Bankruptcy Prediction for Innovative Companies

Ivan Lobeev

Business Analyst, Ramax international, Moscow, Russia,

ivanlobeev@gmail.com, ORCID

Abstract

The main purpose of this article is to identify the best neural network model algorithm and relevant set of variables for predicting financial distress/bankruptcy in innovative companies. While previous articles in this area considered neural network analysis for large companies from primary sectors of the economy, we take the novel approach of examining the less-explored area of innovative companies.

First, we complete a comprehensive review of the relevant literature in order to define the best configuration of factors which can influence bankruptcy, network architecture and learning methodology. We apply our chosen method to a sample of companies from around the world, from industries which are considered innovative, and identify the dependence of bankruptcy probability on a set of factors which are reflected in the financial data of a company.

Our evaluation is based on the financial data of 300 companies – 50 of them are bankrupts, and 250 are 'healthy'. Our results represent the set of relevant factors for bankruptcy prediction and the appropriate neural network. We have applied a total of 19 factors characterising efficiency, liquidity, profitability, sustainability, and level of innovation. Our proposed analysis is appropriate for all sizes of companies. We provided two models in order to cater for the most confidence in terms of obtained results.

The total predictive ability of the model developed in our research is almost 98%, which is extremely efficient, and corresponds to the results of the most modern methods. Both approaches demonstrated almost the same level of influence of factor groups on final bankruptcy probability.

Keywords: bankruptcy, innovative companies, multivariate discriminant analysis, bankruptcy prediction, efficiency, liquidity, profitability, sustainability, innovation

Introduction

At the beginning of the twentieth century, the world economy was faced with a large number of crises. This fact is obviously related to the rapid development of different branches of the economy. World GDP and technological innovation is growing faster than at any previous time in history. As a result, business cycle recessions have destroyed many companies and driven many more to bankruptcy. There are several causes of corporate financial distress and it is a difficult concept to define, but it is possible to reveal factors which can be a signal to impending bankruptcy. The definition of the pre-bankrupt condition is a crucial issue for the timely prevention of distress. There are several models which predict bankruptcy with very high accuracy, however, as we consider in greater detail below, such models are oriented on the basis of large industry sectors such as oil, gas, trading, or the entire economy as a whole. Such models are not effective predictors for companies from the most unsustainable economic sectors, e.g. companies to innovative industries. These companies have the highest bankruptcy risks because they necessitate the exploration of unknown economic areas and the creation of new products without any guarantee of profit. High expenditure in terms of research and development (R&D) decrease the free cash flow of innovative firms, and can leads to financial unsustainability and higher distress risk, although not necessarily. The high levels of R&D expenditure can also lead to successful strategic decisions which can improve the company's financial condition. Such expenditure is, in principle, warranted in the innovative sector, as innovative companies invent new technologies, which can improve life quality worldwide. Currently, there are no research studies which contain an adequate model for bankruptcy prediction of innovative companies. This is the reason why the current research is so relevant. The pre-bankrupt condition can be identified by the combination the presence of a set of formal financial factors, and defining this, particularly for innovative companies, is crucial to our task. As such, our research aims to help such innovative companies identify the relevant factors defining a pre-bankrupt condition in their sector.

The *main purpose* of this article is to choose the best neural network model algorithm and relevant set of factors for predicting the financial distress of innovative companies. Our proposed analysis is appropriate for all sizes of companies. It was conducted because the sample is rather small, and division can spoil the network studying.

To complete our task, it is necessary to address a set of issues: to analyse the research studies of previous years from the earliest to the latest, and to trace the development of knowledge in this sphere; to gather the relevant data for so-called 'healthy' companies and for bankrupt companies and identify an appropriate point indicating the beginning of financial distress; to convert this raw data to a data set which is convenient for analysis, to delete the missing values and to calculate the financial ratios and other variables which constitute factors of innovative corporate bankruptcy; to construct neural networks with different settings (e.g. according to architecture, factors, learning algorithm) and choose the most relevant algorithm with the highest forecasting accuracy and the lowest error; and finally, to construct a financial distress prediction model.

The object of this research is a sample of companies from around the world, from industries which are considered innovative. The subject of this article is the dependence of bankruptcy probability on the set of factors which are reflected in the financial data of a company.

The novelty of current research is that the previous articles in this area considered neural network analysis for large companies from primary sectors of the economy. These tend to be complicated models, which mix different tools such as neural network, regression analysis, multivariate discriminant analysis (MDA), and genetic algorithms, but innovative companies, being the most affected by market fluctuations, have not been adequately considered. On a related note, we selected a global sample of companies, because when restricted to the Russian economy alone, there are not enough companies to run the appropriate analysis.

We will analyse the provided data of 300 companies. 50 of them are bankrupts, and 250 are 'healthy'. Our results represent the set of relevant factors for bankruptcy prediction and the appropriate neural network.

Literature review

Since 1968, when the first and the most famous research paper in financial distress forecasting appeared [1–2], methodological approaches in this sphere have run in two directions: market-based methods and accounting based methods.

The market-based models

The market-based approach usually applies the Black – Scholes formula [3] in terms of call-option as a foundation for further analysis. The assumptions behind this method involve a classical version of option valuation theory: i.e. the value of the main variable corresponds to the Brownian motion value of dependent variables as normally distributed. The main factors for market-based models include: firm value, equity value, debt value, volatility of firm value, risk-free rate, and dividend payments.

As can be noticed all the variables can be seen by all people from the financial market. This is the reason such models are titled 'market-based'. The mathematical apparatus can be very complicated for such models, but the idea of defining the financial condition of a company is very straightforward. Quite simply, there is some threshold combination of variable values which gives the estimation of bankruptcy probability. Merton [4] created the first model with a minimal factor set, and subsequently many researchers improved upon this model by imposing new factors [5–9].

The main advantages of this group of methods are the necessity for small amounts of inputted information, availability for almost all people and also presence of a large

number of special computer programs, which allows to calculate financial distress probability very quickly. The disadvantage of such methods is a low predictive ability and an incapability to vary according to different external conditions.

The accounting-based models

The second type of bankruptcy prediction model is accounting based. Two scientists developed this forecasting direction almost at the same time: Beaver [10] and Altman [1]. Altman's article became so popular that modern researchers often refer to it. Altman's approach used multivariate discriminant analysis (MDA) and ran a regression with five factors. The main factors for accounting-based models includes: profit / total assets; profit + taxes / total assets; sales / total assets; equity /liability; working capital / total assets.

After estimating the coefficient for each of these factors, Altman calculated the Z-score and compared it with critical statistics to make a conclusion about financial sustainability of a particular company. This article has motivated other financial distress experts to create predictive models [11]. Extended models have been in development for a long time, and many additional factors were included in MDA. Different factor combinations have been tested, but the predicting accuracy has not exceeded 75–80%.

The described methods have the advantage of simplicity in calculating bankruptcy score and interpreting results. They can be applied across a range of company types, industries, or economic conditions and can accommodate the inclusion of new factors for multivariate discriminant analysis. Some disadvantages of this method are that different samples can show very different results and on average demonstrate quite low predictive ability. However, this does not mean that such models are useless- in fact, the factors used to build them can be used to develop more advanced predictive approaches. The same factors are used in almost all papers devoted to financial distress prediction with neural network analysis as they give the highest accuracy in forecasting. In this paper, the development of artificial network analysis is considered the most effective method to approach evaluation.

The neural network models

The usage of neural networks for analysing financial distress prediction began with the article of Odom and Sharda [12]. The researchers built a neural network with 2-layer perceptron (MLP) and applied the learning algorithm of backpropagation. The input factors were the same as in the modified Altman model. The factors used in the modified Altman's bankruptcy model include: EBIT / total assets; equity / debt; sales / total assets; working capital / total assets; retained earnings / total assets.

The purpose of Odom and Sharda's article was to compare the predictive ability with the factor set of described neural network and classical MDA model. The data sample was not so large. It comprises 129 large companies from Moody's database, one half of which are bankrupts, with

the rest being 'healthy'. The empirical study results demonstrate the superiority of neural network-based analysis to the MDA model in such aspects as prediction accuracy (79% against 75%), and the robustness of received estimations.

This research showed that there is a more efficient method than the MDA. For the next five years, scientists experimented with changing the factor combination and adding factors to improve the neural network model [13–15]. As a result, the authors managed to increase the predictive accuracy to approximately 80–83%.

It was obvious that corporate bankruptcy prediction required innovative, more convenient approaches to neural network analysis, and the thrust of the research focused on the integration of existing forecasting methods. Lee, Han & Kwon [16] combined neural networks, MDA, and decision trees in their research. They distinguished and compared the predictive ability of five models: MDA, decision trees, neural network with factor selection algorithm based on MDA, neural network with factor selection algorithm based on decision tree, and neural network with a self-organising Fisher's maps (SOFM). MDA and decision trees demonstrate very poor accuracy, about 70–75%. The main interest of their research is the comparison of the quality of three neural network models. The novelty of the research paper is its introduction of an unsupervised learning algorithm. It is widely recognized that in general there are two types of learning algorithm – supervised and unsupervised. The supervised algorithm is the most popular for forecasting. The backpropagation (BP) and learning vector quantisation (LVQ) are related to the supervised method. While SOFM is unsupervised. Lee, Han & Kwon invented a new methodology, combining the SOFM and LVQ, and this model has demonstrated its superiority in comparison to MDA and decision trees-based neural networks. The algorithm of this innovative approach is rather complicated. At the first stage, the neural network with SOFM algorithm factors are allocated to clusters which can reflect almost the same influence on financial sustainability according to input data. The second stage is the neural network analysis with an LVQ learning algorithm. This is needed for choosing the most appropriate variables inside each cluster. The third stage of analysis entails constructing the neural network for defining the most relevant clusters for the sample. The last stage of empirical analysis involves drawing conclusions about whether the company is bankrupt or not. This research was based on a sample of Korean firm data from 1979 to 1992. All companies were arranged according to size and by the value of assets. 58 factors were taken from six spheres: profitability, firm growth, cash flow, stability, activity, and credibility. As a result, the forecasting accuracy of 80.5% was identified, which is greater than other approaches.

The research of Jo, Han and Lee [17] once again proved the superiority of neural networks. They provided a comparison of MDA, case-based approach and neural network. Where previous researchers used linear or hyperbolic tangent activation function, Jo & Han used sigmoid, which is

known today as the greatest resource for predicting bankruptcy. Another novelty is that authors have constructed 36 samples with the data from 1991–1993 for Korean companies. They vary in terms of forecasting period from one to three years. This represents the first research study taking in account the number of years before bankruptcy. As a result, the best forecasting accuracy was rated at a level of approximately 84%.

Yang, Platt and Platt [18] proposed a new type of neural network prediction architecture for financial distress. If all previous authors use multilayer perceptron (MLP) and varied only the learning algorithm, Yang, Platt and Platt used probabilistic neural network (PNN) which is one of a kind of radial basic function (RBF). This type of network is known to be better suited for classification issues. The data sample consists of gas and oil industry companies from the USA over the period of 1984–1989. This methodology exceeds the predictive power of MLP neural networks and especially MDA.

A significant research study which answers questions about the best existing neural network model is the paper of Charalambous, Charitou & Kaourou [19]. They built neural network to define the influence of 7 factors. Factors from the Charalambous, Charitou & Kaourou model include current liabilities / total assets; cash / total assets; long term debt / total assets; operating income; change in cash flow from operations / equity value, change in account receivables; working capital / equity value.

These factors include a comparison of a feedforward neural network architecture with a backpropagation learning algorithm, with a conjugate gradient algorithm, the radial basis function architecture (RBF) with the backpropagation algorithm and the MLP architecture with a combination of SOFM and LVQ. As a result, almost 90% accuracy was obtained for this neural network type. According to the authors, this approach is the most accurate currently in existence.

A number of other research studies approve the fact of superiority of neural network prediction against MDA and other approaches. A Spanish sample was used by Olmeda and Fernandez [20] for predicting financial distress by MDA, decision trees, and an MLP neural network. The latter showed the greatest forecasting power, with 83%. The same accuracy was obtained by Piramuthu, Raghavan and Shaw [21] which analysed the financial sector with MLP. Zhang [22] created the MLP with three hidden layers to predict bankruptcy for Korean firms with Altman's factors. They managed to produce results at 88% accuracy.

Koh and Tan's research [23] studies MLP neural network and profit regression analysis. This concludes that the predictive power is the same for both methods at a 92% level. Hybrid neural network models were constructed in papers of Yang [18] and Yim and Mitchell [24]. Both research studies obtained 95% accuracy. Data from Hungarian companies was introduced in the paper by Virag and Cristofs [25] in the context of a model quality comparison, using a neural network and a math statistical model. The neural network showed superior results.

Tsai and Wu [26] considered the use of an MLP neural network with one hidden layer. Researchers tested different nodes on this layer, numbered from 1 to 13. The analysis result demonstrates superiority of the 3-nodes MLP to other cases.

Kim and Kang [27] provided a comparison of an MLP neural network with three different learning algorithms: backpropagation, boosting, and bagging. The data sample was composed of Korean companies, and more than 30 factors were selected from seven types of firm's information, including: size, liquidity, leverage profitability, debt coverage, activity, and capital structure. As a result, the bagging algorithm produced the best quality results.

Zhou, Lai and Yu [28] included macroeconomic indicators beside a firm's financial ratios in their analysis. They compare MLP neural networks in the presence of macroeconomic variables. The set of variables are show in Table 1. The extended model demonstrated superior results in accuracy.

Table 1. Factors from Zhou, Lai and Yu model

Equity / Total Assets	Dividend	Sales / Cash
Net Income / Net Sales	Total Debt / Total Assets	Current Liabilities / Total Assets
Cash Flow / Total Assets	Current Assets / Total Assets	Long Term Debt / Total Assets
Cash Flow / Total Debt	Retained Earnings / Total Assets	ROA
Current Ratio	Working Capital / Total Assets	Current Assets / Current Liabilities
Cash / Total Assets	Total Assets	Net Income / Equity
Net Income / Sales	Current Assets / Sales	Working Capital / Sales
Fixed Assets / (Equity + Long Term Debt)	GDP	Consumer Price Index
Personal Income Index	Money Amount	

Kasgari et al. [29] conducted another comparison of an MLP neural network with a probit-regression model. They use only four factors, including sales divided by current ratio, operating income divided by sales, current assets divided by total assets, and total debt divided by total liability. The neural network correctly predicted 87% of bankruptcies, which is higher than the figure for the probit model.

Makeeva and Bakurova [30] compared a neural network with logistic regression using factors from four spheres, including financial leverage, profitability, liquidity, and turnover with a sample of Russian oil and gas industry companies. The most important parameters reflected profitability. As a result, the neural network gave 98% accuracy, better than the logistic model.

Yasnitsky et al. [31] ran a neural network analysis checking the probability of bankruptcy in banks. There were 15 qualitative and quantitative parameters. The accuracy of this model is higher than 90%, which is a great result for such an inconsistent industry.

Azayite and Achchab [32] used data from Moroccan companies and a factor set from a modified Altman's model to construct a hybrid model. The MDA regression helped to identify the best factors for a neural network. An MLP with a backpropagation learning algorithm helped to build the financial distress function, and the neural network calculated the bankruptcy probability with an SOFM algorithm. The distinguishing feature of this research is that the failure of firms has been predicted in 1, 2 and 3 years before the initial moment of bankruptcy. The hybrid model allowed for obtaining the best result for the Altman's factor set. The final prediction accuracy is approximately 95%.

Azadnia, Siabi and Motameni [33] tested the fuzzy neural network approach on a data sample of gas and oil companies from Tehran, and produced a prediction accuracy of 99%. They run an MLP with 3 hidden levels. More than 15 factors from four areas (productivity, asset quality, profitability, and sustainability) were selected.

The main research studies in neural network bankruptcy prediction were considered above. The summary of models, data samples, and results are introduced in Table 2.

Table 2. Summary of existing models

Year	Authors	Approach	Data set	Results
1990	Odom & Sharda	MDA vs. MLP neural network	129 companies from Moody's database	MLP (79%) is better than MDA
1996	Lee, Han & Kwon	MDA vs. decision tree vs. MLP based on MDA and decision tree with SOFM and LVQ learning algorithm	140 Korean companies	MLP with SOFM and LVQ is better (80.5%)
1997	Jo & Han	Case-based vs. MDA vs. MLP network	Korean companies (1991–1993)	MLP is better (83.8%)
1998	Yang & Platt	PNN with backpropagation vs. MLP network based on MDA	122 oil companies from USA (1984–1989)	PNN is better (84.1%)
2000	Charalambous & Charitou	MLP with SOFM and LVQ vs. RBF vs. Feedforward network with backpropagation vs. Feedforward network with conjugate algorithm	139 pairs of USA companies	Feedforward network with conjugate is better (89.6%)
2012	Kasgari & Divsalar	MLP	Iranian data set	(87%) accuracy
2012	Makeeva & Bakurova	MLP network vs. logistic regression	Gas & oil sector	MLP is better (98%)
2016	Azayite & Achchab	MLP with MDA and SOFM algorithm	Moroccan companies	(95%) accuracy
2017	Azadnia & Siabi	Fuzzy MLP network	Tehran companies	(99%) accuracy

The 'innovativeness' factor

As was mentioned above, the distinguishing feature of the present paper is the forecasting of bankruptcy, and the application of this forecast to innovative companies. It is very important to explain the rationale behind company selection. In this research, only innovative industries were selected for analysis. The following list of relevant industry sectors were taken from the article by Makeeva and Khugaeva [34] and standard industrial classification: drugs; computer and office equipment; electric transmission and distribution equipment; electrical industrial apparatus; household appliances; electric lighting and wiring equipment; household audio and video equipment; communication equipment; electronic components and accessories; miscellaneous electrical machinery and equipment; telephone communication; and computer programming, data processing and other computer related services; research, development and testing services.

The next question concerns the determination of some special factors, which can be significant for innovative companies in particular. Unfortunately, there are no research studies which look at the bankruptcy of innovative companies' using a neural network, but some do exist which use an MDA and costs of financial distress as analytical tools. The first mention of innovative firms in terms of bankruptcy probability was made by Opler and Titman [35]. They examined the financial distress of innovative companies, but there were no special factors which distinguished high-tech companies.

A more relevant research method is offered by Zhang [22]. He tried to answer the question about the presence of relationship between the R&D expenditure and bankruptcy probability. The Altman's Z-score was used for this purpose. Authors estimated four regressions with four different innovative company's indicators, including R&D expenditure divided by total assets, by sales, by number of employees, and by R&D capital. R&D capital was also used in the paper by Jo, Han and Lee [17]. The formula for R&D capital is following:

$$R \& DCap = R \& D_t + 0.8R \& D_{t-1} + 0,6R \& D_{t-2} +$$
$$+0,4R \& D_{t-3} + 0,2R \& D_{t-4}$$

As can be seen here, the R&D capital is the sum of R&D investments in the current year, and in the previous four years with defined weights.

Bulot also analysed the factors of innovative companies' bankruptcy. Besides the classical factors like liquidity and firm size, he used the R&D investments and change in investment policy like specific innovative factors. As a result,

R&D investments makes sense in terms of a firm's sustainability.

The major research study which contains the analysis of almost 300,000 firms was described in by Buddelmeyer, Jensen and Webster [36]. This investigated the dependence between a firm's sustainability, investment in innovation, and other company characteristics. The model factors from [36] includes: market factors, which characterise the economy's growth and the environmental conditions; technical efficiency which also includes innovative factors like R&D expenditure and short-term investment activity; relative profitability of a company within the industry; salary in the company scaled by total assets is a proxy of variable costs; firm's access to finance.

There is no reason to consider these factors in detail, but it is important that innovativeness is used as a bankruptcy factor. The higher the investment in R&D, the more stable the company, according to the research results.

Makeeva and Khugaeva [34] estimated the costs of financial distress of innovative companies. They faced the problem of bankruptcy probability evaluation. Four factors for innovative companies were selected, including R&D expenditure divided by total assets, R&D expenditure divided by sales, R&D expenditure divided by number of employees, and R&D capital, which is defined as the sum of R&D expenditure of previous years, multiply by some coefficient, which was described above.

To sum up, there are a lot of research studies which investigate the impact of a firm's innovativeness on its sustainability and bankruptcy probability, but all of them use regression or MDA analysis, or focus on the costs of financial distress evaluation. The present research, by comparison, mixes a focus on innovativeness with the more powerful neural network analysis.

The different research studies into bankruptcy probability were discussed above. There are a lot of different methodologies for running the neural network analysis, and many factors from different areas of a company's financial results. We will consider the identification and choice of these factors and appropriate methods for empirical analysis.

Methodology and data

The bankruptcy factors

Several models were reviewed above, and in the framework of this research, the most relevant of those factors will now be outlined. Generally, this can be divided into five groups: effectiveness, profitability, sustainability, liquidity, and innovativeness (Table 3).

Table 3. Model factors

Factor	Reason for inclusion in the model	Research studies which used this factor	Anticipated influence sign on distress probability
Effectiveness			
Growth rate of net sales	The positive mean of this variable means the firm has growing demand on its product or service, and is a good sign that the company has a great financial sustainability	Tudor (2015), Piramuthu & Raghavan (1998), Olmeda & Fernandez (1997)	–
Sales / Total assets	This ratio reflects the effectiveness of assets usage	Ligang & Lai (2010), Olmeda & Fernandez (1997), Charalambous & Charitou (2000)	–
Profitability			
Net profit / Equity	These two variables reflect how much money the assets and equity generate	Charalambous & Charitou (2000); Ligang & Lai (2010); Azadnia & Siabi (2017); Makeeva & Bakurova (2012)	–
Net profit / Total assets			–
Gross profit / Sales	This is another group of profitability indicators, and demonstrates which fraction comprises the cost of goods and other productive expenditure in total revenue		–
Net profit / Sales			–
Sustainability			
Equity / Fixed Assets	This parameter demonstrates the coverage of fixed assets by equity, and is associated with lower sustainability and higher bankruptcy probability	Ligang & Lai (2010), Kim & Kang (2009), Piramuthu & Raghavan (1998), Charalambous & Charitou (2000)	+
Working capital / Total assets	Greater working capital related to assets, and is associated with greater ability to close the budget gaps and greater stability	Azayite & Achchab (2016), Kim & Kang (2009), Charalambous & Charitou (2000)	–
Total liability / Total equity	Less debt in relation to assets and equity, usually associated with greater sustainability of a company and, consequently, with less probability of financial distress	Makeeva & Bakurova (2012), Olmeda & Fernandez (1997), Charalambous & Charitou (2000)	–
Total liability / Total assets		Kasgari & Divsalar (2012), Kim & Kang (2009), Charalambous & Charitou (2000)	–
Liquidity			
Cash / Current liabilities	The most liquid asset is cash, which means that greater value of these two ratios associated with greater liquidity and less bankruptcy probability	Azadnia & Siabi (2017); Tsai & Wu (2008), Piramuthu & Raghavan (1998)	–
Cash / Total assets			–

Factor	Reason for inclusion in the model	Research studies which used this factor	Anticipated influence sign on distress probability
Curent assets / Current liabilities	This parameter group demonstrates the coverage of quick liabilities, total debt and total revenue by liquid assets. A greater mean of these ratios is associated with less bankruptcy probability	Kasgari & Divsalar (2012); Ligang & Lai (2010), Kim & Kang (2009), Charalambous & Charitou (2000)	–
Current assets / Total liabilities			–
Current assets / Sales			–
Current liabilities / Equity	Thus parameter has negative influence on financial sustainability of a company		+
Innovativeness			
R&D / Total assets	The main criteria of innovativeness is R&D expenditure, to eliminate the influence of firm's size, this variable are scaled to total assets and sales	Makeeva & Khugaeva(2018), Liu (2011), Zhang (2005), Bulot (2015)	+/–
R&D / Sales			+/–
RD Capital / Total Assets	RD Capital = R&DExp(t) + 0,8R&DExp(t-1) + 0,6R&DExp(t-2) + 0,4R&DExp(t-3) + 0,2R&Dexp(t-4) This is a cumulative variable of R&D expenditure also scaled by the size		+/–

The above analysis on the anticipated impact of each factor on bankruptcy probability allows us to make a hypothesis about the total influence on each factor's group on final forecasting.

Hypothesis 1. *The effectiveness of a company is negatively related to distress probability for innovative firms.*

Hypothesis 2. *The profitability of a company has the same impact sign.*

Hypothesis 3. *Sustainability has a negative impact on financial distress probability.*

Hypothesis 4. *The liquidity of a company has the same impact sign.*

The innovativeness of a company does not have an obvious impact on performance indicators. Higher R&D expenditure usually affects free cash flow, and as a result the company can become incapable of making necessary payments and can face bankruptcy. On the other hand, greater R&D expenditure may help the firm's management to invent some new product or make some improvements in production processes which can enable growth in the firm's market position and, as a result, outperform its financial variables. Consequently, the probability of bankruptcy can decrease. In the framework of this paper, the following hypothesis is proposed:

Hypothesis 5. *Higher innovativeness is positively related to bankruptcy probability, particularly for companies from innovative industries.*

The neural network's learning

This section is considers different neural network methodologies. The neural network is a model of the neural system of a living organism. In contrast to parametric approaches to forecasting, when the connection between different elements is obvious, the network can identify dependence in cases where it is not straightforward. The network has the ability to learn based on real data in order to successfully forecast further work. Neural networks can be divided into two groups: 'supervised' and 'unsupervised'. The majority of articles considered above used the supervised method. The most popular are the backpropagation (BP) algorithm and learning vector quantisation (LVQ). As the unsupervised algorithm is usually self-organising, Fisher's map is used (SOFM). Several other learning algorithms exist besides these, but they are usually used for other issues, and rarely for forecasting bankruptcy. Moreover, they demonstrate less predictive ability and less robustness in terms of result. The classic BP algorithm was used in terms of network construction because the data have been taken for different sizes and company types. There is one danger in the use of the BP algorithm, which is overlearning. This situation is where the model becomes too formal and inflexible and can only classify bankruptcy according to one factor (whereas it is necessary to take all factors into account). The network usually tries to minimise the error, but while searching for the minimum error point it can overlearn. To eliminate this issue, it is necessary to restrict the learning time and check the model quality according to independent data.

Types of neural network architecture

The multilayer perceptron (MLP)

Another issue which should be taken into account is network architecture. There are several types, but the most popular is multilayer perceptron (MLP). It has at least three layers: input, output, and hidden. The input layer consists of factors and take a data with some weight. The next step involves transferring this weighted data to the hidden layer with an activation function. The neurons involved in the hidden layer can then connect with the output layer with another activation function. The output layer calculates the final mean, and a researcher can make a decision about the financial condition of a company. Neural networks usually contain one hidden layer, but in some cases two of them are needed. Three or more layers are used very rarely. The MLP can use BP, conjugate gradient, or delta-delta as a learning algorithm. The most common is BP. It can use four common activation function types: sigmoid, hyperbolic tangent, threshold, and linear function. The most popular is sigmoid function. This methodology has the main disadvantage of tending towards overlearning, but is consistent in application. This means that MLP greatly analyse the data with large number of input factors.

Radial basis function (RBF)

This function type has exactly one hidden layer with radial function, which produces a Gaussian function. The advantages of RBF are that it has only one hidden layer and it is not necessary to select the number of these layers, also such network entails less learning time, which substantially decreases the possibility of overlearning. The main disadvantage of this architecture type is the sensitivity to the number of factors on input layer. As a result, the network quality usually falls.

Probabilistic neural network (PNN)

Yang, Platt and Platt [18] used the PNN and compared its effectiveness with MDA and MLP. They conclude the superiority of the PNN. This neural network type looks like on RBF – it also has only one hidden level and has the same radial function as activation. PNN has a probability of belonging to some category in contrast to RBF. This architecture is the best for solving the classification issues. It seems this network type is the best for our current research, but poses the disadvantage that PNN can result in low forecast quality because the great number of factors mitigates against the choice of MLP, which is universal and more suitable for current issue.

Other network architecture types

It is necessary to consider other widespread neural network types, including general regression (GRNN), linear (LNN) and the self-organising Kohonen's network. The GRNN is not suitable for bankruptcy prediction. LNN is very simple for this issue. The Kohonen's algorithm was used in some

papers on this topic but it is very difficult to apply, and not needed for the present research framework.

It is quite challenging to construct the best neural network for a particular issue. Because of this, several types of architecture and activation functions were used to build the most appropriate network. MLP perceptron was tested with 1 or 2 hidden layers with different numbers of neurons, as well as various activation functions: sigmoid, hyperbolic tangent, and the Softmax function from SPSS. To run the network, the computer program IBM SPSS Statistics 24 was used.

Data description

For our neural network analysis, we examined data from 300 companies around the world from the innovative sectors. The sample is divided into two groups: bankrupts and 'healthy' companies. There are 51 bankrupts (17%) and 249 'healthy' firms (83%).

 In previous studies an equal proportion of company types was used, but it decreases the model's robustness depending on the choice of sample. Neural networks can predict bankruptcy only where there is an obvious feature of a bankruptcy available to identify. The greater fraction of non-bankrupts with increasing number of observations provide a higher model quality. This is true, because a neural network that can properly classify a bankrupt by a large number of unauthorised bankruptcies is more preferable. Data has been collected for a 6 year period. Thus, we have data on bankrupts for the period of 2012–2017. This long duration was selected because there are not so many companies in these innovative industries which faced with financial distress. The division of companies by bankruptcy is as follows: 2012 – 15, 2013 – 1, 2014 – 8, 2015 – 4, 2016 – 5, 2017 – 8, non-bankrupts – 249.

The division by country is as follows: 126 companies (42%) are from the USA, 66 (22%) – from Canada, 36 (12%) – from China, 21 (7%) – from Japan, 15 (5%) – from South Korea, 36 (12%) – from other countries.

The data sample is divided between 10 industries: computer programming – 117 companies, drugs – 90 companies, communication equipment – 30, electric transmission and distribution equipment – 18, electronic components and accessories – 15, electrical industrial apparatus – 9, R&D and testing services – 6, computer and office equipment – 6, electric lighting and wiring equipment – 6, and household audio and video equipment – 3 (Figure 1).

The observations above are used for our neural network learning and testing sample construction. A total of 37 factors were selected that could affect the likelihood of bankruptcy. The data were taken for two years: a year before the bankruptcy and a year of bankruptcy. Variables and their descriptive statistics are demonstrated in Table 4.

Figure 1. Data sample division by industries

- Computer programming
- Drugs
- Communication equipment
- Electric transmission and distribution equipment
- Electronic components and accessories
- Electrical industrial apparatus
- R&D and testing services
- Computer and office equipment
- Electric lighting and wiring equipment
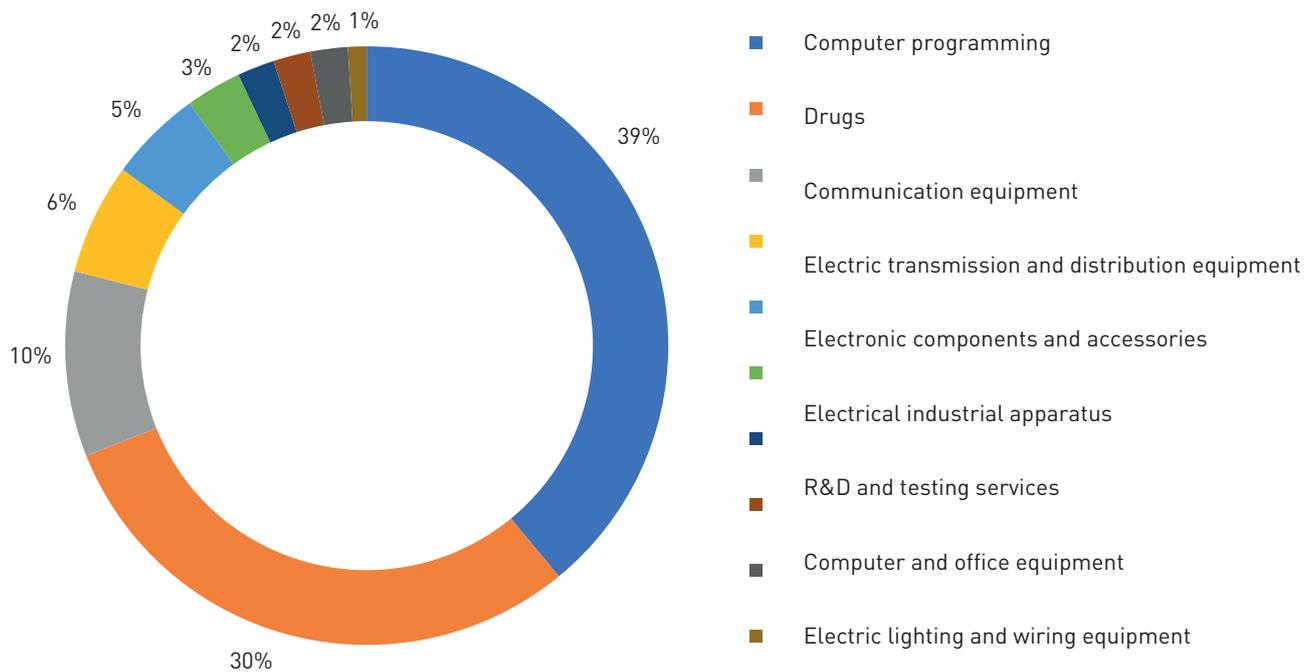
Table 4. Descriptive statistics

		N	Min Value	Max Value	Mean	St. deviation
Descriptive statistics						
BANKRUPT	Bankruptcy	300	0	1	.17	.376
GROW_NS	Growth rate of net sales	295	−.88	11.55	.1524	.79154
GROW_NS1	Growth rate of net sales – 1	295	−3.68	4.93	.0867	.49046
SAL_TA	Sales / Total assets	300	.00	8.06	.8303	.85799
SAL_TA1	Sales / Total assets – 1	300	.00	18.48	.8905	1.31510
NP_E	Net profit / Equity	300	−683.0	210.37	−5.688	55.04891
NP_E1	Net profit / Equity – 1	300	−172.6	11.71	−.7521	10.30278
NP_A	Net pofit / Total assets	300	−11.92	3.63	−.2875	1.23403
NP_A1	Net pofit / Total assets – 1	300	−19.19	3.63	−.3107	1.53507
GP_SAL	Gross profit / Sales	295	−2.90	5.65	.4087	.47648
GP_SAL1	Gross profit / Sales – 1	295	−2.90	5.65	.4154	.47369
NP_SAL	Net profit / Sales	299	−357.8	1.61	−2.606	22.14058
NP_SAL1	Net profit / Sales –1	299	−357.8	1.61	−2.529	21.88535
E_FA	Equity / Fixed assets	295	−2485	433.33	1.0213	153.47650
E_FA1	Equity / Fixed assets – 1	295	−195.5	433.33	9.8318	42.83228
WC_A	Working capital / Total assets	300	−12.00	.86	.1071	1.21998
WC_A1	Working capital / Total assets – 1	300	−17.36	.86	.0302	1.63675
L_E	Total liability / Total equity	300	−171.4	52.28	.4164	10.80219
L_E1	Total liability / Total equity – 1	300	−12.50	55.87	1.2758	5.06943

Descriptive statistics		N	Min Value	Max Value	Mean	St. deviation
L_A	Total liability / Total assets	300	.01	14.13	.7313	1.60268
L_A1	Total liability / Total assets – 1	300	.01	18.05	.7952	1.92696
CASH_CL	Cash / Current liabilities	300	0	19.61	1.0662	1.94487
CASH_CL1	Cash / Current liabilities – 1	300	0	25.57	1.1635	2.18065
CASH_A	Cash / Total asset	300	0	.88	.1984	.17610
CASH_A1	Cash / Total asset – 1	300	0	.88	.2091	.18456
CA_CL	Current assets / Current liabilities	300	.02	31.99	2.7156	3.15632
CA_CL1	Current assets / Current liabilities – 1	300	.01	26.51	2.7648	2.93711
CA_A	Current assets / Total assets	300	.04	1.00	.5876	.22893
CA_A1	Current assets / Total assets – 1	300	.04	.99	.5844	.23206
CA_SAL	Current assets / Sales	299	.03	81.79	1.7277	5.49972
CA_SAL1	Current assets / Sales – 1	299	.01	113.89	1.7283	6.90768
CL_E	Current liabilities / Equity	300	−171.4	36.32	.0948	10.32491
CL_E1	Current liabilities / Equity – 1	300	−5.52	36.32	.8132	3.16743
RD_A	R&D / Total assets	298	0	2151.26	15.768	139.76863
RD_A1	R&D / Total assets – 1	298	0	2204.48	14.413	137.25719
RD_SAL	R&D / Sales	297	0	79061.1	272.77	4587.37140
RD_SAL1	R&D / Sales – 1	297	0	81017.0	282.31	4700.93926
RDCAP	RD Capital / Total assets	297	0	23282.0	439.22	2200.31142
N valid	Bnkrpty File Dt	286				

The minimum and maximum values for each variable for bankrupts and non-bankrupts are presented in Table 5.

Table 5. Minimum and maximum values separately for bankrupts and non-bankrupts

Variable	Bankrupt		Non-bankrupt	
	Min	Max	Min	Max
GROW_NS	−0.88112	4.926324	−0.56961	11.5467
GROW_NS1	−3.67774	4.926324	−0.88024	3.094905
SAL_TA	0	5.685619	0.02721	8.061818
SAL_TA1	0	18.48214	0.007803	8.061818
NP_E	−683.041	11.7094	−172.632	210.3704
NP_E1	-14.813	11.7094	−172.632	0.873351
NP_A	−11.9189	3.63125	−3.24752	0.323625
NP_A1	−19.188	3.63125	−3.24752	0.323625
GP_SAL	−2.9	5.647026	−0.11614	0.966102
GP_SAL1	−2.9	5.647026	−0.11614	0.960938

Variable	Bankrupt		Non-bankrupt	
	Min	Max	Min	Max
NP_SAL	−357.835	1.607192	−50.2368	0.613509
NP_SAL1	−357.835	1.607192	−56.362	1.027454
E_FA	−2485	311.5442	−195.592	433.3333
E_FA1	−161.481	311.5442	−195.592	433.3333
WC_A	−11.9957	0.726	−9.10191	0.859479
WC_A1	−17.3644	0.706875	−9.10191	0.855117
L_E	−16.1891	22.6082	−171.481	52.2807
L_E1	−12.4957	22.6082	−1.07746	55.86709
L_A	0.037827	14.12834	0.011731	13.56984
L_A1	0.096296	18.05416	0.011434	13.56984
CASH_CL	0	13.36595	0.006046	19.60759
CASH_CL1	0	7.490566	0.006046	25.57322
CASH_A	0	0.840932	0.004492	0.882122
CASH_A1	0	0.840932	0.005389	0.882122
CA_CL	0.019171	16.64209	0.049778	31.99091
CA_CL1	0.01245	10.16735	0.049778	26.51117
CA_A	0.040431	0.99894	0.059751	0.972441
CA_A1	0.040431	0.987842	0.047756	0.978232
CA_SAL	0.030588	81.78959	0.059144	9.214689
CA_SAL1	0.007488	22.4529	0.059144	113.889
CL_E	−16.161	12.12195	−171.481	36.31579
CL_E1	−5.51718	12.12195	−0.76056	36.31579
RD_A	0	4.174721	0	2151.261
RD_A1	0	4.174721	0	2204.482
RD_SAL	0	77.4717	0	79061.15
RD_SAL1	0	77.4717	0	81017.09
RDCAP	0	892.4	0	23282

All factors which have the negative anticipated relationship with bankruptcy probability demonstrated less minimum values for bankrupts than for non-bankrupts. Variables which have the positive connection: L_A and L_E have less value for non-bankrupts, which is logically reasonable. There is not the same regularity as for the maximum means, but overall non-bankrupts has a higher value for the factors which have a negative anticipated impact on financial distress probability (with the exception of such variables as CA_SAL and CA_A, which represent liquidity). It is also necessary to notice that non-bankrupts have much greater values for parameters which characterise R&D ex-

penditure. This may constitute the signal that R&D has a negative impact on bankruptcy probability.

Econometric analysis and results

Data treatment

Our empirical analysis began with data processing. The raw data contains a lot of missing values. The data division between the bankrupts and non-bankrupts of each year of the analysing period have also been provided. The next step is the calculation of financial ratios for the year of bankruptcy and a year earlier. Only R&D capital scaled

by total assets was calculated for the current year, because this parameter has already contained information about the R&D expenditure of previous years. The emission data analysis does not make sense, because the neural network methodology does not require it. The final sample contains 286 valid observations: 14 were excluded by the algorithm. For the data analysis, the computer program IBM SPSS statistics has been used.

## Neural network configuration selection

Two architecture types have been tested in the article: RBF and MLP. The first step was to define the best architecture type or its combination to solve the particular problem. The main parameters which aid in selecting the model are the percentage of correctly predicted bankrupts, non-bankrupts, and the error function value. We analysed the following combinations of network architectures:

The classical **MLP** network for all factors described in chapter II, which have been automatically set by the program. Predictive results are outlined below. The model quality is very high: the cross-entropy function produced a very low value; the percentage of correctly predicted companies is high: 98.8% for non-bankrupts and 87.5% for bankrupts on the tested sample (Table 6).

Table 6. Classical MLP model results

Model Results		
Learning	Error: cross entropy	6.596
	Incorrect prediction	0.5%
	Learning time	0:00:00.08

Figure 2. Normalised Importance for RBF
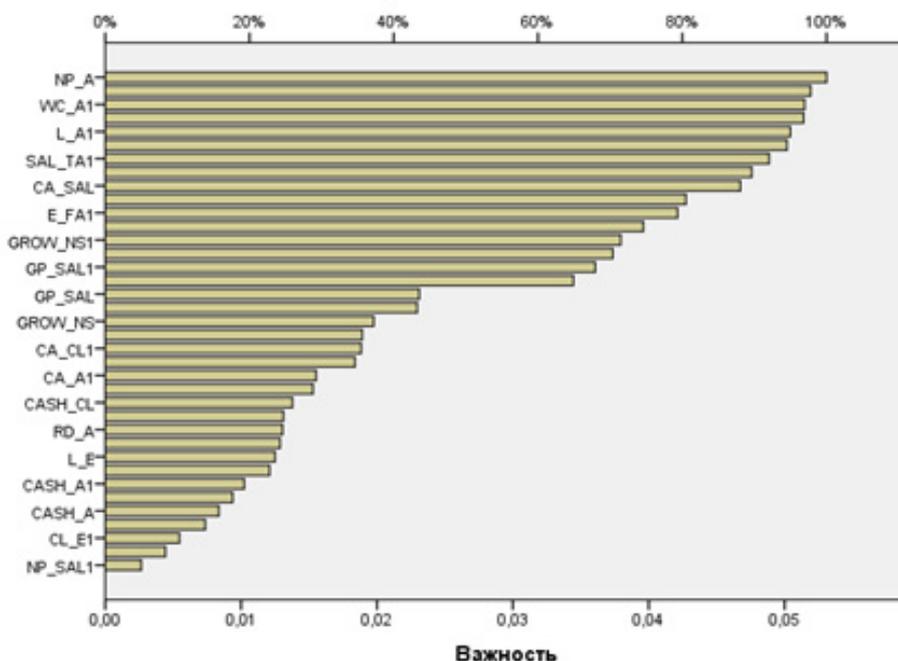
Model Results		
Testing	Error: cross entropy	4.523
	Incorrect prediction	2.2%

The radial basis function algorithm **(RBF)** was also run for all factors. The 8-neurons RBF demonstrated a lower predictive ability: 93.8% for non-bankrupts and 72.7% for the bankrupts on the tested sample with more prevalent errors than in the previous case. It may be noted that this model is worse overall in terms of all the applied parameters (Table 7).

Table 7. RBF results

Model Results		
Learning	Error: sum of squares	15.662
	Incorrect prediction	11.3%
	Learning time	0:00:01.69
Testing	Error: sum of squares	4.864[a]
	Incorrect prediction	8.7%

The MLP with only important parameters **(2-step MLP)**. According to this model the most important factors showed by the first MLP model were included in the network. They are introduced below. The program has automatically selected the optimal algorithm, but the accuracy is lower than in case 1 above: 100% accuracy for non-bankrupts and 67.5% for bankrupts. The model quality is also lower than for MLP with all factors (Figure 2).

The RBF with the most important factors, selected by MLP (**MLP-RBF**). It is known that RBF can predict better with low quantity of input variables. As was stated below, the high dimension dramatically decreases the model quality of RBF. To improve this model, the selection algorithm based on MLP was used. This network demonstrated the lowest result from all models. The error function value is also very large (Table 8).

Table 8. MLP_RBF results

Model Results		
Learning	Error: sum of squares	18.878
	Incorrect prediction	11.8%
	Learning time	0:00:00.85
Testing	Error: sum of squares	7.435[a]
	Incorrect prediction	13.0%

The MLP and RBF, using separate factors for the year of bankruptcy and one year before the bankruptcy. There are 4 different models in total. We do not need to describe all these neural networks in detail because all of them demonstrated a much lower quality of model and predictive accuracy. It is necessary to check the decreased dimension models, because in some cases this can improve the result, but according to analysed data it did not produce a positive result.

The analysis which has been run above allows us to conclude that the MLP neural networks are better than the RBF for this particular issue. The main reason is that the number of the factors is rather large, while the methods of dimension decreasing did not improve the results. Another question is the usage of probabilistic neural network (PNN), which was created for solving classification issues. This approach has an RBF framework, and consequently is inappropriate for the present study, which involves a great number of input factors.

MLP architecture selection

It was decided that simple MLP is the best approach to analysing innovative company bankruptcy probability. MLP can have different kinds of architecture, and for this study all combinations were tested, and the best performing were selected. We can vary the following parameters: the activation function on the hidden layer, on the output layer, the number of the hidden levels, the quantity of neurons on each level. The activation function on the hidden level can be the hyperbolic tangent or sigmoid. The choice of activation function on the output layer is wider, and to that end, to the previous two functions were added identical and softmax functions. For the sake of convenience, all these functions are introduced in Table 9.

Table 9. Activation function types

Activation function	Description
Identical	$F(x) = x$
Sigmoid	$f(x) = \left(1 + e^{-x}\right)^{-\acute{a}}$, $\alpha > 0$, The most common function of this type is logistic function
Hyperbolic tangent	$f(x) = \dfrac{\left(e^{x} - e^{-x}\right)}{\left(e^{x} + e^{-x}\right)}$
Softmax	$f_i(x) = \dfrac{e^{x_i}}{\sum_{i=1}^{J} e^{x_i}}$, $i = 1,\ldots,J$ This is generalised for multidimensional case of sigmoid function. In some case it can help to maintain better model quality.

It may be supposed that the identical function is worse than others for output layer activation function because of non-trivial dependence. For the completeness of the analysis all these functions have been tested.

Another parameter which can be variable in its effects is the layer quantity. For the purposes of forecasting, one or two hidden layers are used. After more than 200 iterations, two optimal configurations of architecture were defined.

MLP with one 4-neuron hidden layer, activation function for hidden layer is hyperbolic tangent, and for output layer Softmax is used. The correctly predicted variables are presented in Table 10. The cross-entropy value is 6.6 for the testing sample and 4.5 for tested. This small error value indicates that the quality of the model is excellent. Moreover, reducing the error value is an excellent feature of network power prediction.

Table 10. One hidden layer MLP results

	Observed	Predicted		
		0	1	Correctly
Learning	0	167	1	99.4%
	1	0	29	100.0%
	Total	84.8%	15,2%	99.5%
Testing	0	80	1	98.8%
	1	1	7	87.5%
	Total	91.0%	9,0%	97.8%

The most important factors are from all the main divisions of economic parameters of a company: profitability, effectiveness, sustainability, liquidity and innovativeness. They are arranged in descending order of importance in terms of predictions, but all of them are included in the top set of values. The neuron weights for the most significant factors are presented in Table 11.

Table 11. One hidden layer MLP estimations

Predictor	Predicted					
	Hidden layer 1				Output layer	
	H1:1	H1:2	H1:3	H1:4	[BANKRUPT=0]	[BANKRUPT=1]
Input layer	**GROW_NS1**	−.098	.126	.642	.293	
	NP_E	−1.07	1.00	.823	.737	
	NP_A	−1.02	.122	−.168	.345	
	NP_SAL	−.877	.255	.142	−.147	
	E_FA1	.496	−.201	.338	−.753	
	L_A1	.785	−1.02	−.343	−.305	
	CA_SAL	−.022	−.467	.162	−.738	
	RD_A	−.613	.382	.706	.071	
Hidden layer 1	**H1:1**					−1.153
	H1:2					1.540
	H1:3					1.237
	H1:4					2.018

The negative mean of neuron weight means that the increasing value of input mean decreases the output value. On the other hand, it reflects negative relationships between the dependent variable and a covariate. The positive value indicates a positive relationship. We shall here explore in detail the defining of dependence between NP_E and bankruptcy probability. The neuron on the hidden layer, which has a positive relationship with higher financial distress probability is H (1:1), because of its positive value, other neurons have a negative impact. The NP_E has a strictly negative correlation with neuron H (1:1). It can be concluded that NP_E has a negative connection with bankruptcy probability. It means that the variable NP_E and the company's profitability is the factor which decreases the bankruptcy probability. NP_A and NP_SAL, which also reflect profitability, have the overall effect of decreasing distress probability. The GROW_NS1, which reflects the firm's effectiveness also has the negative relationship with bankruptcy probability. L_A and E_FA1 are the variables from the sustainability sector, but the higher mean corresponds to lower sustainability. The dependence of these factors on bankruptcy probability is positive, and consequently the higher sustainability decreases such dependence. CA_SAL is the liquidity factor. Correspondingly to neuron weights it does not have definite influence, but the total impact is more likely positive than negative on bankruptcy probability. Nevertheless, the influence of liquidity is much less than the impact of profitability. RD_A variable is the innovativeness factor. It has a definite impact on distress probability, which is negative. To sum up, according to this model of the neural network, hypotheses 1, 2 and 3 are not rejected, while hypotheses 4 and 5 are rejected.

MLP with 2 hidden layers, 5 neurons in layer one and 4 in layer two, activation function for hidden layer is sigmoid, and for output layer Softmax is used. The cross entropy is 9.128 for the learning sample and 5.097 for testing sample. It is not significantly higher than in the previous network. The total accuracy is also less overall, but the main advantage of this model is that it has the highest value for correctly predicted bankrupts – 91.7%. The results of all samples are presented in Table 12.

Table 12. Results for MLP with two hidden layers

	Observed	Predicted		
		0	1	Correct
Learning	**0**	181	3	98.4%
	1	0	25	100.0%
	Total	86.6%	13.4%	98.6%
Testing	**0**	64	1	98.5%
	1	1	11	91.7%
	Total	84.4%	15.6%	97.4%

The variables from profitability, liquidity, sustainability, effectiveness and innovativeness are among the most important factors in terms of prediction accuracy, but the order of importance has a different sequence than in previous models. The table listing the influence coefficients on bankruptcy for the main variables is introduced in Table 13.

As can be noticed, profitability again negatively correlates with distress probability: NP_E, NP_A and NP_SAL1 have positive coefficients in relation to the output neurons for non-bankrupts. L_A has a negative coefficient, meaning unsustainability has a negative effect. Consequently, sustainability has a positive impact. Efficiency, Liquidity and innovativeness has also negative influence on bankruptcy probability. To sum up, profitability, effectiveness, and sustainability have a negative impact on bankruptcy probability, as was assumed in our hypothesis. Liquidity has been demonstrated to have a strictly negative impact in the second model, and to not have a strictly defined effect in the first model. As such, we can conclude that there is an overall negative impact on the likelihood of distress. The innovation hypothesis was rejected by both models, and it also has a negative connection. The representation of diapasons for the most important factors for bankrupts and non-bankrupts is presented in Table 14.

Table 13. Two hidden layers MLP factor impact

Factor	Influence
NP_E	35.80942
NP_A	54.17096
L_A	−102.832
RD_A	28.66417
GROW_NS1	27.67251
NP_SAL1	25.55392
WC_A1	40.76026

Table 14. The ranges for bankrupts and non-bankrupts for the most important variables

NP_E				
	Bankrupt		**Non-bankrupt**	
Range	**Frequency**	**Percent**	**Frequency**	**Percent**
−3.67773696	18	35,3	2	0,8
−1.95692485	1	2,0	5	2,0
−0.23611274	8	15,7	25	10,1
1.48469937	16	31,4	215	86,7
3.20551148	4	7,8	0	0,0
4.92632358	4	7,8	1	0,4
	51		248	

CA_SAL				
	Bankrupt		**Non-bankrupt**	
Range	**Frequency**	**Percent**	**Frequency**	**Percent**
0.03058824	1	2,0	0	0,0
16.3823882	45	90,0	249	100,0
32.7341881	2	4,0	0	0,0
49.085988	1	2,0	0	0,0
65.4377879	0	0,0	0	0,0
81.7895879	1	2,0	0	0,0
	50		249	

L_A				
Range	**Bankrupt**		**Non-bankrupt**	
	Frequency	**Percent**	**Frequency**	**Percent**
0.01173083	0	0.0	1	0.4
2.83505311	44	86.3	247	99.2
5.6583754	3	5.9	0	0.0
8.48169768	0	0.0	0	0.0
11.30502	1	2.0	0	0.0
14.1283422	3	5.9	1	0.4
	51		249	

RD_A				
Range	**Bankrupt**		**Non-bankrupt**	
	Frequency	**Percent**	**Frequency**	**Percent**
0	8	16.3	49	19.7
430.252101	41	83.7	197	79.1
860.504202	0	0.0	1	0.4
1290.7563	0	0.0	1	0.4
1721.0084	0	0.0	0	0.0
2151.2605	0	0.0	1	0,.4
	49		249	

GROW_NS1				
Range	**Bankrupt**		**Non-bankrupt**	
	Frequency	**Percent**	**Frequency**	**Percent**
−3.67773696	1	2.2	0	0.0
−1.95692485	0	0.0	0	0.0
−0.23611274	2	4.3	22	8.8
1.48469937	42	91.3	226	90.8
3.20551148	0	0.0	1	0.4
4.92632358	1	2.2	0	0.0
	46		249	

.

The distribution of observations across all ranges is almost the same for all the most important factors. The L_A factor which characterises a company's unsustainability is more likely greater for the bankrupt, which is logically explainable. CS_SAL presents the liquidity and it can be noticed that all non-bankrupts have almost the same level of this parameter, while for the bankrupts means are variously distributed across the ranges. We may conclude that profitability is the most important factor for NP_E as the distribution of values for bankrupts are closer to the lowest range, while healthy firms indicate a higher average mean.

Checking model quality

In the framework of this research, our model's validity needs to be approved. What are the major arguments that these two models can strongly predict distress? First, the demonstration by two different neural networks of practically identical results in terms of influence and importance allows us to conclude that the model is of high quality. Second, the values of the error function and the prediction accuracy are at a high level. But it is not enough to be confident in the quality of the model. There is one problem that remains: that dependence is obvious and a neural network is not needed to predict bankruptcy. In many articles, for example Lee, Han & Kwon (1996) a decision tree analysis was imposed in order to exclude this possibility. In this paper the random forest analysis is provided to prove the model quality. The results are shown in Table 15.

Table 15. The random forest prediction results

Model Results			
Observed	Predicted		
	0	1	Correctly
0	249	0	100.0%
1	51	0	0.0%
Total	100.0%	0.0%	83.0%
Approach: CHAID			

As can be seen here, 83% is the final accuracy level for the decision tree, against more than 98% by both neural networks. The quantity of correctly predicted bankrupts is zero. This fact lends credence to the argument that the neural network is a quality model with great predictive power for both categories. The final question is the choice of the most powerful model among those provided above. Both networks have great predictive power, as well as advantages and disadvantages. To receive a more accurate result for non-bankrupts the first model is preferable, while the second network is more appropriate for predicting bankruptcy.

Conclusion

In recent years, research studies on financial distress predicting have been devoted to increasing forecasting power. Many new combined methods have been invented: MDA with a neural network, more complex network configuration algorithms, networks based on a genetic algorithm, and many others. The total predictive ability of the model developed in the present research is almost 98%, which corresponds to the results of the most modern methods. The multilayer perceptron gave a great result due to the correctly selected factor set and network architecture. The most important factors have been taken from the best models of the earliest research which we have analysed. Moreover, extra factors have been added which reflect the 'innovativeness' of companies, because the paper's purpose was the prediction of financial distress for innovative companies. We have applied a total of 19 factors characterising efficiency, liquidity, profitability, sustainability, and level of innovation. All these factors have been analysed over two specific years: the year before bankruptcy, and the previous one, with the exception of R&D capital, which was examined only for one year. We provided two models in order to cater for the most confidence in terms of obtained results. The 3-layer MLP is greater for predicting all of a company's conditions, while the 4-layer MLP is greater for bankruptcy forecasting (91% correctly predicted bankrupts). Both approaches demonstrated almost the same level of influence of factor groups on final bankruptcy probability. The first model demonstrates a negative impact in terms of sustainability, profitability, effectiveness, and innovativeness, and an inconclusive result in terms of liquidity. The second model demonstrates a negative influence for all factor groups. The most important factors are profitability, sustainability, and innovativeness. Additionally, the variables NP_A, NP_E, L_A, L_A1, L_E, RD_A, CA_SAL and GROW_NS1 demonstrate the highest importance.

It would be very interesting to continue the development of models for innovative companies. Possible improvements involve the following: the expansion of the sample by adding additional years before bankruptcy, the use of dynamic neural networks to analyse this data sample and the introduction of special algorithms for selecting the most appropriate factor. More accurate predictions were possible only with the use of genetic algorithms and fuzzy neural networks, but previous studies used these approaches only for data samples from non-innovative companies. It would be interesting to apply such approaches on the forecast of financial distress of an innovative company.

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