Neural Networks in Credit Risk Classification of Companies in the Construction Sector

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ABSTRACT: The financial sector (banks, financial institutions, etc.) is the sector most exposed to financial and credit risk, as one of the basic objectives of banks' activity (as a specific enterprise) is granting credit and loans. Because credit risk is one of the problems constantly faced by banks, identification of potential good and bad customers is an extremely important task. This paper investigates the use of different structures of neural networks to support the preliminary credit risk decision-making process. The results are compared among the models and juxtaposed with real-world data. Moreover, different sets and subsets of entry data are analyzed to find the best input variables (financial ratios).

JEL classification: G33, C58, G21

Keywords: credit risk, neural networks, financial ratios, credit risk decision-making process

Introduction

The history of bank systems indicates that the main reasons for decreasing potential profits or capital and the occurrence of financial difficulties are an inefficient credit granting policy, faulty credit procedures of credit norms and regulations, and insufficient collateral for loans. In a market economy, risk is a common phenomenon. However, it affects various economic

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branches, and decisions made within them, to a different extent. Taking into consideration that the banking sector has gone through a tremendous evolution and that banks currently offer an impressive array of products, identifying potential 'good' and 'bad' customers is an extremely important task. The reduction of loans granted to companies of questionable credibility can significantly influence and improve banks' performance. Credit risk is broadly conceived as the probability of non-repayment of bank financial resources granted to debtors (enterprises). Every decision based on credit risk should be preceded by close scrutiny. In that analysis, the most important element for categorizing debtors as 'good' or 'bad' is a prior identification of factors that affect the condition of companies. Those factors are traditionally financial ratios.

One must keep in mind that banks constitute the link between borrowers and lenders and that the money granted to borrowers is, in fact, the money obtained by a bank from the deposits made by natural and legal persons. Accordingly, an even bigger responsibility rests with the banks to correctly choose borrowers whose creditworthiness is high. To achieve this goal, banks use different methods to assess customers' creditworthiness (i.e., the probability that the customer will pay back the full amount of the loan and all other contractual payments at a predetermined time). Usually, these methods are credit scoring methods combined with financial ratio analysis and models of discriminant analysis, the objective of which is to assign the potential debtor to one of two groups: 'good' (i.e., likely to repay money loaned) or 'bad' (i.e., unlikely to repay money loaned) customer. However, although these methods are being actively developed to make them more accurate, very often they are still too static when used alone and do not follow the latest trends in a rapidly changing economy and in market conditions, or they do not distinguish among some subtle economic or behavioral factors. Moreover, new approach credit-risk models (i.e., probability of default, standard, or reduced structural models) often appear to be too complex or too dependent on the market. Their complexity and the amount of data needed for their implementation is often a fundamental problem and a barrier to their efficient use on a larger scale.

Currently, risk analysis in the financial markets is one of the most important factors for investment analysis and new methods must be very flexible and adaptive to the changing realities of the market economy. Therefore, a growing interest in solutions such as artificial neural networks and their application to credit risk assessment is noticeable; even the smallest improvement in accuracy is a significant accomplishment. The idea of neural networks as computing processors has its origin in the way the human brain analyzes obtained data. Neural networks in the scientific literature are defined as *'a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs'* (Hecht-Nielsen, 1988). It is important to stress that because the main characteristic of neural networks is adaptation, the abovementioned problems are rarely a concern with these methods. Neural networks can be used in such tasks as pattern recognition, classification, and time series forecasting. They have a built-in capacity to adapt their synaptic weights to changes in the surrounding environment. In particular, a neural network trained to operate in a specific environment can be easily retrained to deal with minor changes in the operating environmental conditions (Haykin, 2011) – the biggest advantage of the method.

The present study is an applied study that uses a descriptive research strategy. A neural network (often referred to as an artificial neural network) technique is used. The main objective of the study is to deliver a useful tool (a set of financial ratios) to business practitioners (e.g., bank analysts), particularly those working in risk departments. This is achieved by meeting two interdependent goals. First, to create a novel set of financial ratios by identifying the most and least important determinants of customers' solvency in the construction sector and, consequently, of their probability of default. Second, to compare the results achieved with two different, commonly used types of neural network and their predictive abilities, on the basis of historical data.

1 Overview of neural networks' use in credit risk evaluation

Neural networks are used world-wide to analyse the scope of credit risks. Atiya (2001) presents an empirical approach based on the relationship between default and the characteristics of a firm learned from the data. The results indicated the superiority of neural networks over other techniques, as well as the need for improvements in training methods, architecture selection, and input, with the latter prompting the author to search for a better method of selection of independent input. Baesens et al. (2003) investigated how neural networks contribute to helping credit risk managers explain why a particular applicant is classified as either bad or good. They concluded that neural network rule extraction and decision trees are effective and powerful management tools, allowing the construction of advanced and user-friendly decision support systems for credit risk evaluation.

Neural networks are particularly suited to analyzing and interpreting complex and often obscure phenomena and processes (Pacelli and Azzollini, 2011). However, as with other methods, neural networks have their strengths and weaknesses, for instance, the fact that it is unknown to the researcher what kind of links and interdependencies are included in the hidden layers (Pacelli and Azzollini, 2011). Nonetheless, research shows that despite the weaknesses, neural networks perform well when data are noisy or incorrect (Angelini et al., 2008; di Tollo, 2006).

Despite much research proving neural networks' usefulness, there are also many criticisms of neural networks. The main disadvantage, which is often brought up in the literature, is the fact that a neural network acts as a 'black box.' Much information is inaccessible to the researcher. Various authors (e.g., Huang et al., 2004; Karaa and Krichene, 2012; Khemakhem and Boujelbene, 2015; Linder et al., 2004; Ogwueleka et al., 2015) have described neural networks and compared them with other modelling techniques, such as decision trees, discriminant analysis, and regression functions, also providing some opinions and critiques of the approach

As described above, many studies have been dedicated to the implementation of neural network analytical methods in business. However, very little has been said about the influence of economic sector on companies' performance and, consequently, on neural network performance and subsequent bank loan-granting decisions and potential losses due to the wrong classification of entities as good or bad credit risks. Furthermore, it is visible in companies' financial statements that the line of business has an effect on the statements' structures and figures. All the above gave the author an incentive to investigate the topic further (see also Wójcicka, 2016a,b). Therefore, choosing the unique set of variables most appropriate for a particular (industrial) sector and implementing it in a neural network is the key objective of this paper.

2 Methods

The analysis conducted for this research was based on the financial reports of Polish companies in the construction sector and the credit risk analysis method applied by one of the banks operating in the Polish market. The choice of the construction sector was dictated by the fact that companies in this sector suffered tremendously from the after-effects of the economic crisis which started in 2007-2008. Many construction sector companies (e.g., developers, main contractors, and sub-contractors) declared bankruptcy. In the tested period, defaults in the construction sector happened more often than in other sectors.[1] Hence, this is one of the sectors which caused banks a lot of trouble. Additionally, no matter how unfavorable the situation was for the banks, it also delivered much valuable data for research (e.g., data on defaulted companies or companies in distress while their situation was rapidly deteriorating soon after the positive decision of the bank). Summing up, it is beneficial to recognize the factors which can indicate future problems in the construction sector.

The tool used in the analysis was Statistica Automated Neural Networks (SANN) and the two neural network structures presented in the paper are multilayer perceptron (MLP) and radial basis function (RBF). MLP neural networks are more powerful than the single-layer

[1] The comparison of default frequency was run for the construction, trade, and industrial sectors.

models which construct linear decision boundaries. MLP can be trained as a discriminative model to yield class posteriors. There are a variety of non-linear activation functions that may be used (Migdał Najman and Najman, 2013; Osowski, 2006; Ripley, 2009; Wantoch-Rekowski, 2003; Witkowska, 2002). The RBF (multilayer and feed-forward) is often used for strict interpolation in multi-dimensional space (Osowski, 2006; Ripley, 2009; Skubalska-Rafajłowicz, 2011; Wantoch-Rekowski, 2003).[2] The main differences and similarities between the two types of neural network architecture are presented in Table 1.

The data used in the analysis were obtained from a bank operating in the Polish market, from the Commercial Court in Poznań,[3] , and from NOTORIA SERWIS (a financial data vendor in Poland). The data cover a period of six years (2009-2014). The sample contains financial statements of construction companies, which include a balance sheet, an income statement, a cash flow statement, and a statement of changes in equity. All the data (regardless of source) were verified to ensure comparability. The verification involved establishing whether the above-listed financial statements provided the data needed to calculate the 25 financial ratios (independent variables) shown in Table 2. If the statements were incomplete, then the company was rejected from the sample.

This initial set of 25 ratios was used as the entry data in the neural network learning process. Twenty neural networks, each based on one of the two chosen artificial neural network models – MLP and RBF – were estimated to determine the value of the dependent variable for the analyzed company. Then, the iterative process of reducing the set of entry data began. The first step was to calculate the correlation between each pair of ratios. Next, the pair with the highest correlation was chosen. From that pair, the ratio with the highest average level of absolute value of correlation with the remaining ratios was rejected. The resulting set of 24 ratios was then input as entry data into the neural network learning system. The same process was used to reject another ratio and that set of 23 ratios applied as entry data for the neural network. This process was continued until the results of the neural networks indicated overfitting, at which point it was stopped. Although the process of ratio selection might seem independent from the neural networks, it is not entirely so because the outcome of the neural networks' performance is its stopping point.

The dependent variable identified the company as 'good' or 'bad.' A 'bad' enterprise was defined as one that either had been declared bankrupt or where a bankruptcy petition had been filed. In turn, a company that had not been declared bankrupt and where no petition for bankruptcy had been filed was defined as a 'good' company.

The data was applied to the two chosen artificial neural network models to estimate whether the analyzed company was 'good' or 'bad.' The whole sample of unsound companies

[2]https://documents.software.dell.com/statistics/textbook/neural-networks#multilayera.
[3]The names of the companies cannot be revealed due to confidentiality restrictions.

included 408 entities. However, some financial statements were incomplete and thus made it impossible to calculate all necessary ratios. Also, to be included in the analysis, the company's financial statements had to be accessible for a minimum of three years.[4] There were 88 companies that failed to satisfy at least one of the requirements and were removed from the analysis.

For each unsound company included in the analysis, a similar healthy company was added (for a total of 320 healthy companies). Similarity was assessed in terms of belonging to the same branch of the construction sector, value of total assets, and legal form. The entire dataset – a whole, homogenous, and balanced sample of 640 companies – was divided into three groups in the following manner:

a. a learning group (80% of dataset);
b. a testing group (10% of dataset); and
c. a validation/holdout group (10% of dataset).[5]

The learning and testing groups consist of the data from the court and NOTORIA SERWIS; however, the validation group is the mix of financial statements of companies from the bank and court data, providing data of good and bad companies, respectively.

For building the models, different variants of hidden layers were used. The number of nodes in a hidden layer is selected automatically. In the output layer, the dependent variable is the category of a customer (good or bad).

3 Findings

In the process of ratio selection, the rejected ratios were as follows (in order of rejection): quick ratio, stock turnover ratio, gross profit margin ratio, equity debt ratio, short-term investments turnover ratio, equity profitability ratio, sale profitability ratio, self-financing ratio, operating ratio, sales dynamics, receivables to liabilities ratio, costs increase ratio, long-term debt ratio, debt/EBITDA, EBITDA/financial expenses, current assets turnover ratio, and operating activity profitability ratio.

It appears that the best set of ratios for MLP consists of eight following ratios (in order of importance based on the SANN sensitivity analysis): current ratio, receivables ratio, net profit margin ratio, financial surplus rate, total debt ratio, costs level ratio, assets profitability ratio, and financial leverage. However, in two instances, the MLP neural network which performed better than the other analysed MLP networks consisted of nine ratios (the additional ratio being operating activity profitability ratio).

[4]The bank requires financial statements of a company for a three-year period to assess the credit risk.

[5]A testing group tests the quality of the neural network during the learning process. The validation dataset is a separate dataset, which is not used during the learning process.

In the case of RBF, the neural network includes a slightly larger set of ten ratios, which includes the operating activity profitability and current assets turnover ratios in addition to the above eight ratios. In this case, there also were some notable exceptions in a number of ratios among the best-performing neural networks. In one case, the set was enlarged by the EBITDA/financial expenses ratio and in another, the current assets turnover ratio was removed from the set of ten.

Each learning process included 20 neural networks for each subset of ratios. The results shown in Tables 3 and 4 present the five highest quality (or best) neural networks for each model structure.[6] The networks are presented in the following way: X-Y-Z, where X equals the number of inputs, Y the number of neurons in the hidden units, and Z the number of outputs (taking values: 'healthy' and 'unsound', respectively).

In terms of the results in a learning group, it is certainly the MLP 8-11-2 network which performs the best, reaching 96.67% accuracy, although the level of accuracy of the best RBF network (10-13-2) is quite similar at 95.00%. The range in learning accuracy levels for the group of the five best networks is wider in the case of MLP (from 81.67 to 96.67, or 15 points) than in the case of RBF (from 85.0 to 95.0, or 10 points). This indicates a certain instability in the results. However, the best accuracy in the testing groups is the same (91.67%) in both types of neural network model.

The next step was to compare the performance of the best neural network of each type (i.e., MLP 8-11-2 and RBF 10-13-2) with the final set of selected ratios on a separate set of input data (the validation group) from the construction sector. This step was taken because the economy and companies' performances are undergoing a constant process of change. Very rarely, it might happen that a company would be evaluated more than once on the same set of data or that two companies were exactly the same when it came to their performance, although in general, even if a company were to have tried several times to apply for financial means from the same bank, this would probably have involved financial statements from various time periods. Therefore, the validation group used an input dataset that was separate from the learning and testing group, although included analogous financial ratios as indicated by the best neural networks. This multi-step procedure was designed to imitate a real process of credit risk validation in a bank wherein we input new data (i.e., the financial ratios of a new applicant/company) into a neural network (tool) that has already been trained in advance.

This approach proved that both types of neural network show good results; however,

[6] The term 'quality' refers to a combined measure (e.g., the expected loss from combined type I and II errors) showing the overall performance of the chosen network. The measure is calculated based on the results of the 'confusion matrix' which shows both the number of correctly classified and incorrectly classified cases per category (see more at http://documentation.statsoft.com/STATISTICAHelp.aspx?path=SANN/Ratios/SANNExamples_HRatio).

MLP performs slightly better than RBF. This was assumed on the basis of the degree of type II error, which means the degree to which banks fail to identify bad customers and instead falsely identify them as good customers, therefore accepting their applications and granting financing, which is likely to lead to a bad customer's insolvency and bankruptcy. Table 5 presents the results of type II error for both types of tested neural network.

As type II error is considered to be more significant for the banks, the results in table 5 justify the belief that MLP networks would be preferred to RBF for credit risk assessment, as the level of that type of error is lower in the case of this neural network type (10.0% compared to 13.3%). Type I error was not considered as it is less harmful for the bank. Although the rejection of good customers (if falsely identified as bad) can cause the bank to lose a significant amount of money in the form of 'lost opportunities,' this is seen as 'a virtual loss.'

The results presented in Table 5 were also compared with a real credit decision-making system (from here on referred to as the bank credit scoring method-BCSM). The sets of ratios used in MLP, RBF, and BCSM are presented in Table 6.

The BCSM uses the six following ratios: current ratio, quick ratio, financial surplus rate, total debt ratio, debt/EBITDA, and net profit margin ratio. Specified ranges for these ratios are set in advance by the bank. After calculating the required ratios and classifying them as falling into the specified range or not, a decision on the potential borrower's credit rating is made by an analyst according to the financial performance (ratios) and the analyst's experience. However, the ratios used are invariable, regardless of the line of business of the borrower. This could be a significant drawback as many sectors operate under specific conditions that may not apply to other sectors.

As seen in Table 6, the model which uses the smallest number of ratios is BCSM (six ratios). MLP uses eight ratios, and RBF uses the same set as MLP with the addition of two extra ratios. Only four ratios are shared by all three models. BCSM, based on the same set of input data, performed similarly to RBF, reaching a level of 13.33% for type II error. Therefore, the following conclusions can be drawn:

• Each tested model seems promising concerning the credit risk decision-making process as the obtained results are accurate (all of the models in the validation group exceed the level of 85%).
• A greater number of ratios used in the model does not guarantee a more accurate result; although RBF uses ten ratios, its results are slightly less accurate than, for instance, the results of MLP with eight ratios.
• On the other hand, a smaller (or in this case, the smallest) number of ratios also does not improve the results. BCSM uses the smallest number of ratios (six), but its results in the

validation group are identical to those of RBF (86.67%).

• The worse performance of BSCM, which is supposed to be tailor-made for the purpose, can be explained by the fact that it does not recognize the line of business and implements the same set of inputs (ratios) for all companies across all sectors.

• Although MLP is considered slower in learning than RBF, this fact seems to positively influence the final results, with MLP showing a higher accuracy RBF (90.0% and 86.67%, respectively).

Summing up, it is important to point out that both neural network types perform very well on a new set of data. This is both remarkable and also very useful in real life as the network is taught on historical data and then used to make decisions concerning new applications.

Another approach to selecting ratios for rejection was also implemented. It was based on a sensitivity analysis of the neural network obtained during the learning process. Sensitivity analysis in data mining and statistical model building generally refers to the assessment of the importance of each of the predictor variables in the fitted models. Given a fitted model with certain model parameters, for each predictor it presents what the effect would be of varying the parameters of the model (for each variable) on the overall model fit. In SANN, the program computes the sums of squares residuals or misclassification rates for the model when the respective predictor is eliminated from the neural net. Ratios (of the reduced model versus the full model) are also reported, and the predictors can be sorted by their importance or relevance for the particular neural network. In the research, after each process of learning, a sensitivity analysis of the input data (financial ratios) was performed. However, as useful as the tool might seem, a significant obstacle was encountered during the analysis. The problem appears when the neural network does not indicate any ratio as unnecessary which, in turn, leaves a large set of input data which, theoretically, should remain unchanged. This stopping point was reached when MLP rejected ratios until 19 remained and RBF did so until 17 remained. The results obtained by these depleted networks were of good quality. However, they did not exceed the results of either MLP 8-11-2 or RBF 10-13-2. Therefore, that path of analysis was not continued and those results are not presented. The conclusions drawn from this analysis are as follows:

1) Neural networks do not always reject the input data which might seem irrelevant.

2) Neural networks do not reject input data which seem to be duplicated (in the case of the input data from this research, for instance, two ratios: current and quick).

3) Neural networks do not always have the ability to distinguish the data, the rejection of which could improve the final results.

Concerning the above, it seems necessary to choose the input data carefully. It might also be useful to use some methods of data selection prior to neural network implementation as, according to the research, the neural network is not always able to eliminate the data, the rejection of which could improve the network's performance.

4 Conclusions

Making a wrong credit decision can result in large financial losses. Therefore, credit risk estimation and correct classification of customers is a valid, current, and significant issue. Many different ways of categorizing accounts are used, ranging from experts' opinions, credit scoring methods, Z-score models, and other individual models implemented by banks. Among these models are neural networks which, in recent years, have gained in popularity. Their performance is good, and they are effective at classifying customers and credit risks as they possess a built-in capacity to adapt their synaptic weights to changes in the surrounding environment and can be easily retrained to deal with minor changes in the operating environmental conditions. The research shows that for various structures of neural networks, different sets of variables should be used to improve the final results.

The set of input data for this study was selected from the construction sector, and proved to include information beneficial to the performance of the neural networks (MLP and RBF), particularly when compared to the results of the method used by a bank to classify customers to an appropriate group (BCSM). The analysis of the results of all three methods (two different architectures of neural networks and BCSM) indicates that banks should consider adjusting their models in relation to companies from different sectors of the economy.

The research also shows that techniques used for prior selection of input data and rejection during the process of learning are required. Neural networks with a smaller number of financial ratios delivered better results than the ones in which there were more ratios and where input data overlapped. However, the sensitivity analysis in SANN was also sufficient to achieve the goal of data selection.

One of the further directions indicated by this research is a comparative analysis among neural networks and other approaches to categorizing clients: credit scoring, Z-score models, and other classification methods (e.g., classification trees and regression). Another direction is to extend the financial analysis of ratios and to decide whether each business sector should be evaluated on a separate subset of data or whether a universal set of financial variables exists which can be used regardless of the line of business.

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Table 1: Comparison of multilayer perceptron (MLP) and radial basis function (RBF) neural networks

Feature of network architecture	**Neural network type**	
	MLP	**RBF**
Signal transmission	Feed-forward	Feed-forward
Process of building the model	One stage	Two different independent stages: • First stage: the probability distribution is established by means of radial basis functions • Second stage: the network learns the relations between input x and output y Note: The lag is only visible in RBF in the output layer
Threshold	Yes	No
Type of parameters	Weights and thresholds	• Location and width of basis function • Weights binding basis functions with output
Functioning time	Faster	Slower (bigger memory and size required)
Learning time	Slower	Faster

Source: own, on the basis of Bishop (1995); Haykin (2011); Migdał Najman and Najman (2013); Skubalska-Rafajłowicz (2011); West (2000).

Table 2: Financial ratios used as independent variables

1	Current ratio	14	Financial surplus rate
2	Quick ratio	15	Long-term debt ratio
3	Receivables ratio	16	Current assets turnover ratio
4	Stock turnover ratio	17	Short-term investments turnover ratio
5	Receivables to liabilities ratio	18	Operating activity profitability ratio
6	Gross profit margin ratio	19	Assets profitability ratio
7	Net profit margin ratio	20	Equity profitability ratio
8	Sale profitability ratio	21	Costs increase ratio
9	Costs level ratio	22	Sales dynamics
10	Total debt ratio	23	Operating ratio
11	Equity debt ratio	24	Self-financing ratio
12	Financial leverage	25	EBITDA/Financial expenses
13	Debt/EBITDA		

Note: *,**,*** denote significance at 10%, 5% and 1% levels. Standard errors in brackets.

Table 3: Highest quality multilayer perceptron (MLP) neural networks

Rank	Neutral Network	Quality (learning) %	Quality (testing) %	Function of error	Activation (hidden layer)	Activation (output)	Additional ratio
1	MLP 8-11-2	96.67	90.00	Entropy	Sinus	Softmax	-
2	MLP 8-12-2	95.00	91.67	Entropy	Sinus	Softmax	-
3	MLP 9-10-2	93.33	88.33	SOS	Logistic	Linear	Operating activity profitability ratio
4	MLP 9-13-2	86.67	80.00	SOS	Exponential	Sinus	Operating activity profitability ratio
5	MLP 8-9-2	81.67	78.33	SOS	Tanh	Exponential	-

Table 4: Highest quality radial basis function (RBF) neural networks

Rank	Neutral Network	Quality (learning) %	Quality (testing) %	Function of error	Activation (hidden layer)	Activation (output)	Additional ratio
1	RBF 10-13-2	95.00	91.67	Entropy	Gaussian	Softmax	-
2	RBF 10-12-2	93.33	91.67	Entropy	Gaussian	Softmax	-
3	RBF 10-10-2	88.33	83.33	Entropy	Gaussian	Softmax	-
4	RBF 11-14-2	88.33	81.67	Entropy	Gaussian	Softmax	EBITDA/ Financial expenses ratio
5	RBF 9-12-2	85.00	81.67	Entropy	Gaussian	Softmax	(Current assets turnover ratio)*

Note: *Without indicated ratio.

Table 5: Type II error for multilayer perceptron (MLP) and radial basis function (RBF) networks

Type of neural network	Type II error (%)
MLP	10.00
RBF	13.33