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OPTIMIZING THE CAPITAL STRUCTURE OF THE COMPANY TO MAXIMIZE ITS PROFITS BY USING NEURAL NETWORKS ON THE EXAMPLE OF BUILDING COMPANIES

Abstract. *Nowadays, there are many methods meant for the optimization of an enterprise capital structure. Thus, the aim of this contribution is to find the most efficient way of a company's possession capital structure. The article simply strives to find such a capital structure that ensures an adequate profit, respectively equity evaluation provided for money. For this purpose, balance sheets, respectively their parts informing about the sources of enterprise financing and the results, respectively only the total profit after taxation of all enterprises running their business between 2006 to 2015, will be used. To find the model neural networks will be used – specifically a multi-layer perceptron network and a neural network of a radial basic function. A neural network which will help a construction company find a suitable financing source structure so, that it could reach the requested ROE of 10%. The model will be useful not only for a building company management but also for evaluating its performance and health by the competitors, creditors or suppliers.*

Key words: *Artificial Neural Networks, Capital, ROE, model.*

Introduction

Capital structure is one of the key aspects for a successful operation of any company. Optimal capital structure decision of a company affects its continuity and financial performance. According to [1] capital structure is targeting long-term funding sources used by companies to finance their development and to increase their market value. Capital structure refers to the proportion of debt and equity in financial structure, and it is of great importance fort company operation, and development to maintain good capital structure [2]. In [3] says that to make optimal capital structure, it is necessary to minimize the capital cost, decrease definite risks under existing limits, and maximize profitability. In [4] indicate that companies operating in different industry have different capital structure. Capital structure should be a compromise between risk and profitability. The growth of debt capital share increases risk and at the same time raises profitability of equity capital. Companies using only equity capital have maximal financial stability (equity to total assets), on other hand, considerably decrease the development rates losing additional source of financing assets growth [5]. The optimal capital structure is a combination of equity capital and debt capital (Leverage ratio) that provides maximal market-value capital of the company (and company value as a whole). Capital structure is affected by most of company-specific factors such as tangibility, non-debt tax shield, liquidity, firm size, taxes paid, profitability and growth asset [4].

There are many theories addressing capital structure management. It is difficult to formulate a general theory of optimal capital structure because there are many factors that could explain the financing of companies [6]. Nowadays there is no universal and uniquely reliable way how to optimize company capital. Therefore, we use in the calculations several models that offer a different view on the capital structure, to ensure the multidimensionality and comparability when optimizing the capital structure [7]. Generally, they may divided into two groups – static theories and dynamic theories. In the [8] divided this theories to the trade-off theory and pecking order theory. These are two basic frames in which the capital structure should be managed. The trade-off theory emphasizes taxes and their effect on the capital structure. The packing order theory puts emphasis on availability of information and thus the information asymmetry [9]. In most of the empirical studies on capital structure determinants authors use models which involve the regression of the observed leverage ratio against a number of microeconomic or firm-level explanatory variables [10].

The capital provided for remuneration generates costs that reduce profits [11]. In practice, with this logic began to use the concept of weighted average costs of capital (WACC). However, its disadvantage can be seen both in that it involves to the calculation capital provided for remuneration and, secondly, in the way it calculates and predicts (albeit using other tools) price for usage of foreign capital and especially equity. At an incorrect estimate, the evaluator obtains unrealistic or even absurd results.

According to [12] one of the most important indicators, which measures the performance (profit) of the company is Return On Equity (ROE). Using ROE can determine whether the company is profit-maker or, conversely, does not generate profit [13]. Indicator find the following formula:

$$ROE = (Earning\ After\ Tax\ /\ Total\ Equity) * 100 \tag{1}$$

Suitable result should be ROE, which is higher than 12% [14]. However, for the purposes of this contribution it will be considered for successful the company, that achieves the rate of return on equity of 10% and higher.

To optimize the capital structure can also use other methods. For example, favourite is an artificial intelligence – namely Artificial Neural Networks (ANNs). These systems are inspired by biology – neurology. ANNs have ability to learn, to generalize the data, remember them, produce new information (self-learning, self-organizing, and self-adapting) and especially, they have a high ability to analyze large volumes of data [15]. Although neural networks often outperform traditional statistical methods, they have some disadvantages. They are not good at explaining how they reach their decisions or their performance can be hindered because of failings in the use of training data – using smaller data sets [16]. To find an effective model for optimization of the capital structure will be used two types of ANNs: Multilayer Perceptron Neural Networks (MLP) and Radial Basic Network (RBF).

The aim of this paper is to find an effective way to optimize the capital structure of the company assets. For capital will be considered in this contribution, all sources of funding of the company. Companies are founded to generate profits. Therefore, we seek a capital structure that will guarantee a reasonable profit, respectively evaluation of equity provided for remuneration. We assume that determine the target value of individual capital components. According to own preferences then the company determine its content.

1. Material and methodology

For the purpose of calculation the data of building companies operating in the CZ between 2007 to 2016. Specifically, these are companies included within the CZ-NACE (Economic classification of field activities in the CZ) in the F section. Specifically, it will be the following data:

1. Profit and Loss: Operating Economic Result in thousands of CZK: it the result of the enterprise´s activity given by the difference of costs and profits relating to the main process of the enterprise, i.e. the conversion of production factors to products.
2. Balance-sheet: The volume of input equity in thousands of CZK: it is capital put in for money (a profit share). Only capital related to the right to vote at the company´s General Meeting and thus the possibility to participate at the company business management is taken into account.
3. Balance-Sheet: Foreign Capital (only charged) in thousands of CZK: again it is capital charged in the form of paid interest.

If all information is considered according to companies and years, 65 406 record lines are available. However, it is completely inappropriate to work with incomplete data from Albertina database, which is the source of the data. If we leave out all the lines from the set in which at least one detail needed for the calculation is missing, we will get 23 998 record lines. The difference between the size of the previous and newly acquired set may be mark das wrong data. It is, however, necessary to realize that due to the incompleteness of the data and partially also due to the reduction of incomplete lines the required result may be distorted.

For the purpose of calculation, DELL Statistica Software in version No. 12 will be used. Specifically, it will be a datamining tool – neural networks. It is a regression for the calculation of which the ´automated neural network´ tool will be suitable. Enterprise debt will be used as an independent variable, and weighted average capital costs as an (in) dependent one.

The data will be divided into three groups:

1. Training: 70%,
2. Testing: 15%,
3. Validation: 15%.

The seed for random choice was set at the value of 1000. Downsampling will be run randomly. In order to set the suitable regressive neural structures multiple perceptron networks will be used (´MLP´ further on), and neural networks of the radial basic function (´RBF´ further on).

In the case of multi-layer perceptron networks, a minimal amount of 2 neurons has been set for the hidden layer, and the maximal amount of 50. In RBF at least 4 neurons and maximally 8 neurons will be used.

Neural structures will be set in both hidden layer and in the output layer of the neural structure as activating functions:

1. Identity,
2. Logistic function,
3. Hyperbolic Tan,
4. Exponential Function,
5. Sinus.

Other setting will be default.

2. Results – production function

Table No.1 gives basic descriptive statistics of a data set, respectively of independent variables (basic capital, charged foreign capital) and a dependent variable (operating activity economic result) for all the three data variables (training, testing and validation).

Table 1 – Basic Data Statistics

Samples	Data Statistics (Building Enterprises)		
	Basic Capital	Bank Credit and help	Operating Economic Result
	Input Variable	Input Variable	Output (Aim)
Minimum (Training)	-287836	-24866	-163349
Maximum (Training)	15080300	4367451	1246902
Average (Training)	8782	11670	3655
Standard Deviation (Training)	129205	83150	26988
Minimum (Testing)	-212230	-9416	-413003
Maximum (Testing)	1386200	3167252	1369411
Average (Testing í)	6602	10920	3698
Standard Deviation (Testing)	52393	79542	32425
Minimum (Validation)	-235570	-46681	-159210
Maximum (Validation)	1521145	3116051	936875
Average (Validation)	8439	13575	4707
Standard Deviation (Validation)	44292	100638	20211
Minimum (Overall)	-287836	-46681	-413003
Maximum (Overall)	15080300	4367451	1369411
Average (Overall)	8404	11843	3819
Standard Deviation (Overall)	112629	82679	28772

Source: Author

Based on the applied methodology five best generated neural networks were generated and preserved. Their registry and characteristics are given in Table No. 2.

Table 2 – A Summary of Acquired Neural Networks

In.	Network Name	Train. Perf.	Testing Perf.	Valid. Performance	Training Fault	Testing Fault
1	MLP 2-6-1	0,500464	0,489215	0,577862	272970489	403832710
2	MLP 2-3-1	0,469041	0,486239	0,612480	284430339	410272698
3	MLP 2-3-1	0,517988	0,488193	0,577589	268720294	401832556
4	MLP 2-8-1	0,500726	0,479586	0,581045	275028902	405649658
5	MLP 2-3-1	0,466950	0,459770	0,578683	285789497	415747087

In.	Network Name	Validation Fault	Training Algorithm	Fault Function	Activ. in the Hidden Layer.	Output Activ. Function
1	MLP 2-6-1	371584978	BFGS (Quasi-Newton) 58	Sum of Squares	Tanh	Sinus
2	MLP 2-3-1	369067729	BFGS (Quasi-Newton) 54	Sum of Squares	Sinus	Expon.
3	MLP 2-3-1	360506478	BFGS (Quasi-Newton) 36	Sum of Squares	Logistic	Expon.
4	MLP 2-8-1	361834669	BFGS (Quasi-Newton) 28	Sum of Squares	Expon.	Expon.
5	MLP 2-3-1	373302998	BFGS (Quasi-Newton) 24	Sum of Squares	Sinus	Logistic

Source: Author

Only three-layer perceptron networks are preserved among the most successful networks. No neural network of the radial basic function has been preserved. All networks prove two input neurons and logically one output neuron. Mutually they differ in the amount of neurons in the hidden layer and in activation functions in the hidden layer and in the output layer. All networks use Quasi-Newton (BFGS) as the training algorithm.

The next step is correlation coefficients between the independent variable and a dependent variable always for one preserved network, in the training, testing and validation set of data.

If we ordered the individual networks according to their success we would chose the third MLP 2-3-1 network as most successful. The first network, MLP 2-6-1 follows, and the second network, MLP 2-3-1. Differences between MLPs are almost imperceptible. In general, the correlation coefficients prove quite a low rate of interdependence. Although the dependence is obvious the practical use of acquired neural structure may be questionable.

Interesting results offers the sensitivity analysis. It is sensitivity analysis of generated and preserved neural networks. To carry out the analysis only training sets of data were used in all the cases of networks.

From sensitivity analysis it is clear that the Operating Economic Result is dependent especially on the used basic capital. It is quite clearly proved that interest resulting from using such capital influences the company´s economy much more. Only in the case of fourth network dependence of operating economic result is almost the same in both components of the capital.

Than we bring the characteristics of individual data sets according to the generated and preserved multiple-layer perceptron networks.

The results will help us specify which of the preserved structures is most appropriate. Surely we should observe residue values. We are looking for the lowest residues in the minimal values as well as for the lowest residues in maximal values, ideally in the training data sets. Residues are relatively similar in all networks. In case of minimal residues the worst result proves, according to correlational coefficients the most successful network. In other values the networks are similar. In my opinion, it is impossible to state which network will be the most successful. It is possible to sum up that all networks will probably have a similar performance in optimizing enterprise capital structure.

Conclusion

The aim of the contribution was to find an artificial neural structure which would serve the enterprise in optimizing its capital structure. Yet the optimal capital structure should be characterised by the enterprise´s ability to generate the highest profit. The calculation was supposed to be carried out on the example of building companies.

The aim of the contribution was fulfilled. 1000 neural structures were generated, out of which best 5 were preserved. Having analysed the partial characteristics of each, it was clear that the performance of all preserved networks was similar. Unfortunately, the coefficients of correlation between tested variables did not prove optimal values. Although the dependence was proved it is not significant enough. Thus, it is necessary to consider the use of this model in practise. Tuning out the individual models seems to be the easiest way. It is not however completely sure whether the required effect will be reached. It is possible to:

1. Adjust the input data set. The set proved shortcomings. Data was missing. It is possible that the set contained false data.
2. Use a bigger rate of individual capital account detail. The contribution works with capital on the level of synthetic accounts (equity, foreign charged capital). I tis possible that some components of capital prove a higher rate of correlation with the operating economic result in comparison to others.
3. Based on sensitivity analysis, to adjust partial vector weights in chosen structures.

It is very probable that after tuning-out the generated and preserved neural structure will be able to prove such a performance to make the model capable of use within a real enterprise.

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