UDK 004.942

Z. ROWLAND, J. VRBKA

OPTIMIZATION OF A COMPANY´S PROPERTY STRUCTURE AIMING AT MAXIMIZATION OF ITS PROFIT USING NEURAL NETWORKS WITH THE EXAMPLE OF A SET OF CONSTRUCTION COMPANIES

***Abstract**. This contribution tries to find an efficient way of a company´s property optimization. It searches for such a property structure that would ensure adequate benefit, respectively, the appreciation of own capital provided for remuneration. To carry out the calculation balance sheets, respectively their parts informing about the company´s property are used, as well as income statements – the total taxed profit of all companies running their business in the CZ from 2006 to 2015. To find the model artificial neural networks are used – specifically a multi-layer perceptron network and a neural network of a radial basic function. The result is a neural structure that will help the building company find a suitable property structure, so that the company reaches the required ROE of 10% (a company is considered successful, if it reaches 10% and more on Return on Equity). The model is useful not only in company management but also in evaluating its performance and health by competitors, creditors or suppliers.*

***Key words**: property, ROE, artificial neural networks, model.*

Introduction

The branch of construction belongs to the most demanding business branches in general. In the article [1] characterizes building companies, as specific companies dealing with building production. Especially in comparison to the industry, but also to another branch, the building industry is characterized by a wide range of specifics some of which may negatively influence its economy [2]. According to [3] the difference of building companies from others is seen mainly in the following: in the individual character of the product, organization of production process, length of production cycle, mobility of the producer and stationarity of the product and lower capacity use. In [4] adds the composition of property structure among other differences or characteristic features. That should be chosen appropriately to reach the long-term maximization of profit.

In the article [5] states that a company´s property structure is possible to be understood from the balance sheet and is composed of two aggregated components, in other words, fixed assets and current assets. According to [6] it is typical for building companies to possess a significant share of current assets while the greatest item of building production is made of stock, without a doubt. Due to this fact it is very important to control their correct management. In case the company binds more than needed it acts inefficient [7].

The main aim of a building company´s origin and pursuit is, as in any other company´s case, is reaching the highest efficiency of input capital possible. That must be ensured especially by the company prosperity, which will be reached by building company profitability [6]. Companies are founded exactly in order to generate profit. One of the most important indicators for the measuring of a building company´s performance (profit), which is most interesting for managers, shareholders and investors, is the indicator of Return on Equity (ROE). ROE basically represents the measure of how efficiently the company uses the shareholders´ means to consequently generate profit [8]. In [9] claims that through ROE it is possible to determine whether the company is profit creator or whether, on the contrary, it does not generate profit.

ROE indicator will be found through the following relation [10]:

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

According to [11] Return on Equity rate may be considered positive in case its value is higher than 12%. For the purpose of this article a company will be considered successful if it reaches 10% and more of ROE.

In today´s modern world the number of companies, using ANNs (Artificial Neural Networks) to find a suitable and efficient way of property structure optimization [12]. In [13] claims that it was possible to meet these systems, computer software working on the basis of special mathematic algorithms, respectively, for the first time in the area of neurology. According to [14] ANNs are characterized especially by their high ability to analyse a huge volume of information. Other abilities of artificial neural networks, according to [15] include the abilities to learn, to generalize data, to memorize, to produce new information, etc.

The MPL Multi-Layer Perceptron Neural Network and RBF – Radial Basic Network may be classified among the most frequently used neural networks [16]. These two types of ANNs will be used throughout this article to find a model which would optimize a company´s property efficiently. In [17] characterize MLP as a forward artificial neural network which consists of at least two layers of perceptrons (neurons). In each layer all inputs of individual neurons are connected to the outputs of the previous layer. The outputs head towards the following layer only [18]. According to [17] MLP is a modification of a classic linear perceptron and it is able to differentiate information impossible to be separated linearly. The RBF neural network has a similar structure to the previous networks. That one is, according to [19] composed of two layers of forward networks and is used mainly for approximation function and a time line of prognoses, for classification and clustering of tasks (interpolation, time line modelling, speech distinction, 3D modelling, data fusion).

The aim of this contribution is to find an efficient way of a company´s property optimization. Thus, such a property structure that will ensure an adequate profit, with the example of building companies in the Czech Republic.

1. Material and methodology

For the purpose of analyzis the data of building companies in the Czech Republic, from 2006 to 2015, has been chosen. Specifically, they are companies classified in the Building F section, i.e. [20]: ′This section includes specialized as well as non-specialized building activities. They include new-building works, repairs, building extensions, reconstructions, engineering works, building of pre-fabricated objects in the construction-site, and temporary buildings.

These include the building of complete flat, office and shopping-mall buildings, other public buildings, agriculture buildings, sports halls and gymnasiums, etc., on the one hand, and the building of highways, roads, bridges, tunnels, railways, runways, ports and other aquatic constructions, irrigation canals, sewerage, industrial objects, conduits and power lines, open sports stadiums and playgrounds, etc., on the other hand.′ We were interested in the data of the companies, such as identification number, name of the given company, the amount of current assets in thousands of CZK, the amount of fixed assets in CZK, profit or loss of the given company.

The data file will thus create a table where the line will represent the company and a specific year of economy. In total, the file contains 66 743 of record lines. Records of companies in disposal and records of companies terminating their activity in the given year (potentially extreme values) were removed from the file.

Our aim is basically finding the production curve that uses two inputs – current assets and fixed assets. At the same time, we are looking for such a combination of inputs that will bring the most optimal profit (respectively production) to the building company.

To prepare the data file MS Excel will be used. For the purpose of the calculation the DELL Statistica software in version No. 7 and 12 will be used. Consequently, it will be processed through automated neural networks.

Used variables are continuous. Thus, we will use a module of time series used through regression. The data will be divided into three groups:

– Training: 70%,

– Testing: 15%,

– Validation: 15%.

The seed for a random selection was determined at a value of 1000. Downsampling will be run randomly.

Consequently, 1000 random artificial neural structures will be generated, out of which 5 most appropriate results will be preserved[1].

These kinds of neural networks will be used:

1. A neural network of Radial Basic Function (further as RBF),
2. A multi-layer perceptron neural network – three-layer (further on as MLP).

We will use the following: linear function, step function, saturating linear function, sigmoid function and hyperbolic tangent function as an activating function in a hidden and output layer of neurons.

In the hidden RBF layer up to 9 neurons will be used. In the hidden layer of the three-layer perceptron network up to 20 neurons will be used. Other settings will be default.

[1] We will determine this through the smallest squares method. If the differences between newly generated networks will be no more significant the training session will be ended.

2. Results and Discussion

The data was divided into three sets – training, testing and validation. The choice was carried out randomly. Based on the data sets 1000 neural networks were generated. Five of them were preserved – those with the best statistics. An overview of the obtained and preserved neural networks is given in Table No. 1.

Table 1 – An overview of generated and preserved neural networks

In	Name of Network	Train. Performance	Test. Performance	Valid. Performance	Train. Fault	Testing Fault
1	MLP 2-8-1	0,664731	0,618323	0,766145	193071859	104324593
2	MLP 2-6-1	0,667188	0,620293	0,766498	191987650	103794019
3	MLP 2-9-1	0,664684	0,620674	0,765502	193079223	103764588
4	MLP 2-7-1	0,664716	0,619914	0,765698	193104285	103932935
5	MLP 2-17-1	0,667793	0,621257	0,766153	191653012	103637452

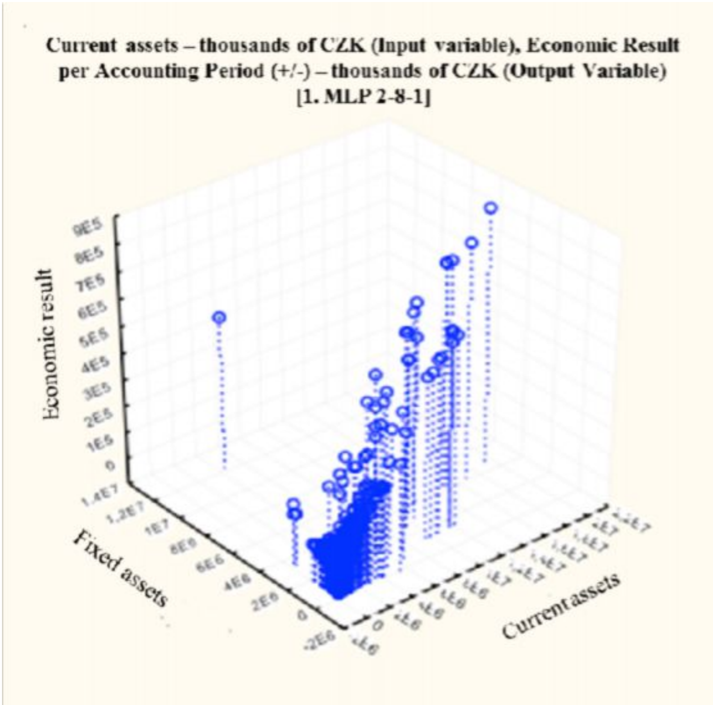
In	Name of Network	Validation Fault	Train. Algorithm	Fault Function	Activ. Hidden Layer	Output Act. Layer
1	MLP 2-8-1	74849911	BFGS (Quasi-Newton) 9	Sum of Squares	Logistic	Tan
2	MLP 2-6-1	74658406	BFGS (Quasi-Newton) 18	Sum of Squares	Tan	Tan
3	MLP 2-9-1	74901561	BFGS (Quasi-Newton) 10	Sum of Squares	Sinus	Logistic
4	MLP 2-7-1	74873824	BFGS (Quasi-Newton) 8	Sum of Squares	Sinus	Logistic
5	MLP 2-17-1	74741476	BFGS (Quasi-Newton) 15	Sum of Squares	Tan	Logistic

Source: Authors

It is interesting that all preserved neural networks are based on a multi-layer perceptron neural network. The table proves that all exhibit similar characteristics with regard to performance and fault, in all three data sets. Individual networks only differ in the activating networks used in the hidden layer of neurons and in the output layer of neurons. In the hidden layer of neurons, they use a logistic function, a hyperbolic tan and the sinus function. Hyperbolic tan and logistic function, are then used in the hidden neural layer. Thus, at the first sight we could generalize the fact that MLP is suitable for regression tasks.

Further, correlation coefficients of all generated and preserved networks were analysed, having been divided into training, testing and validation set of data. It may be deduced from the results that in all three sets of data there exists a correlation. Yet it is not so high. It moves throughout sets and individual networks from almost 0.62 to almost 0.77. A comparison descriptive characteristics among individual data sets follows. It is clear that partial results are relatively similar. Although they do differ in some items, the differences are not significant.

In Figure No. 1, to get a better idea, we may observe the distribution of current asset combinations, the distribution of fixed assets and building companies′ profit in the CZ, predicted by the MLP 2-8-1 network. Similarly, the distribution of current assets´ combinations was created, as well as the distribution of fixed assets and the profit of building companies in the CZ, predicted by the rest of the chosen neural networks.



Source: Authors

Figure 1 – Combination of Current Assets, Fixed Assets and Profit of building companies in the CZ according to the MLP 2-8-1

Prediction differs from the reality only in lower values of current assets and in lower values of fixed assets. In higher values prediction reaches reality very closely. Models even respect the deviated value, when the company generated profit at a low volume of current assets and at a high volume of fixed assets. It may be assumed that if the data was divided into four quadrants:

1. A high volume of current assets and at the same moment a high volume of fixed assets,
2. A high volume of current assets and at the same moment a low volume of fixed assets,
3. A low volume of current assets and at the same moment a high volume of fixed assets,
4. A low volume of current assets and at the same moment a low volume of fixed assets.

We would find out that the highest level of correlation may be reached in quadrant No.1. It would be followed by quadrants no. two and three. The fourth quadrant would be correlated the least.

To verify this idea, we created a sensitivity analysis of economy result based on partial input variables. Profit is based on both input variables. It depends much more on the volume of current assets where the values move around the interval of more than 1.641 to almost 1.675 thousand of CZK. In case of fixed assets, the values move around almost 1.007 up to almost 1.027 thousand CZK. The result also reflects the current structure of building companies´ property, where a huge volume is made of fixed assets.

Conclusion

The aim of this contribution has been to find an efficient way of optimization of a company´s property. Thus to find such a property structure that would ensure an adequate profit based on the example of building companies in the Czech Republic.

The aim of the contribution has been fulfilled. 1000 neural structures were generated out of which five with the best characteristics were preserved. With regard to a not-entirely-satisfactory correlation among the input and output variable a closer analysis of interdependence of individual variables had to be carried out. Thanks to that it turned out that the generated and preserved models were much more exact if they predict the results of large enterprises, i.e. enterprises with a large volume of current and fixed assets. Moreover, the analysis clearly proves that the company´s economic result is much more sensitive towards changes in current assets volume than towards the changes of fixed assets volume. Thus a clear recommendation towards capital goods consumption management is given – towards the company´s cost policy. Building enterprises have to strive to be as efficient as possible working with material in construction sites. Fixed assets consumption is fixed.

The results offer a clear direction for the purpose of another paper – to divide building companies into smaller groups according to their size. Further, it would be suitable to pay attention to partial property items.

Models as such are not very useful in practice at the evaluated detail rate. Yet they do allow us to guess, having carried out the above-mentioned changes, a large potential for enterprise management (especially in case of large enterprises).

REFERENCES

1. Hoffmann, S., Wicke, D., & Cadez, I. (2015). Survey of sustainability in construction companies. Bautechnik, 92(10), pp. 725-729.
2. Vochozka, M. & Stehel, V. (2012). Regionální disparity ve vývoji stavebního odvětví v České republice. [Regional disparities in the development of the construction sector in the Czech Republic]. Littera Scripta, 5(2), pp. 187-202.
3. Horta, I., & Camanho, A. (2013). Company failure prediction in the construction industry. Expert Systems with Applications, 16(40), pp. 6253-6257.
4. Lehutová, K., Križanová, A. & Klieštik, T. (2013). Quantification of Equity and Debt Capital Costs in the Specific Conditions of Transport Enterprises, In: Proceedings of the 17th International Conference on Transport Means, Transport Means. Kaunas, Lithuania, pp. 258-261.
5. Wong, W. P., Gholipour, H. F., & Bazrafshan, E. (2012). How efficient are real estate and construction companies in Iran's close economy? International Journal of Strategic Property Management, 16(4), pp. 392-413.
6. Yang, Z., Lin, L., & Li, H. (2010). Ownership Structure and Financial Reporting Transparency: The Empirical Evidence from Construction and Real Estate Listed

Companies in China. Proceedings of the 2010 International Conference on Construction and Real Estate Management. Brisbane, Australia, pp. 816-820.
7. Siskina, S., Juodis, A., & Apanaviciene, R. (2009). Evaluation of the competitiveness of construction company overhead costs. Journal of Civil Engineering and Management, 15(2), pp. 215-224.
8. de Wet, J. H. V. H., & du Toit, E. (2007). Return on equity: A popular, but flawed measure of corporate financial performance. South African Journal of Business Management, 38(1), pp. 56-69.
9. Kijewska, A. (2016). Determinants of the Return on Equity Ratio (Roe) on the Example of Companies from Metallurgy and mining sector in Poland. Metalurgija, 55(2), pp. 285-288.
10. Vojteková, M, Bartošová, V. (2009). Comparability and mathematical aspects of the use of indicators of financial analysis in the evaluation of the company. Ekonomicko-manažerské spektrum, 3(2), pp. 72-76.
11. Ichsani, S., & Suhardi I, A. R. (2015). The Effect of Return on Equity (ROE) and Return on Investment (ROI) on Trading Volume. Procedia – Social and Behavioral Sciences, 211, pp. 896-902.
12. Wilczyńska-Piliszek, A. J., Piliszek, S., & Falandysz, J. (2012). Use of quantitative-structure property relationship (QSPR) and artificial neural network (ANN) based approaches for estimating the octanol-water partition coefficients of the 209 chlorinated trans -azobenzene congeners. Journal of Environmental Science and Health, Part B, 47(2), pp. 111-128.
13. Izeboudjen, N., Larbes, C., & Farah, A. (2014). A new classification approach for neural networks hardware: from standards chips to embedded systems on chip. Artificial Intelligence Review, 41(4), pp. 491-534.
14. Mileris, R., & Boguslauskas, V. (2011). Credit Risk Estimation Model Development Process: Main Steps and Model Improvement. Engineering Economics, 22(2), pp. 126-133.
15. Luzar, M., Sobolewski, Ł., Miczulski, W., Korbitcz, J., Díaz Lantanda, A., Munoz - Guijosa, J. M., & Muňoz Sanz J. L. (2014). Prediction of corrections for the Polish time scale UTC (PL) using artificial neural networks: from standards chips to embedded systems on chip. Lubrication Science, 26(3), pp. 141-162.
16. Michal, P., Vagaská, A., Gombár, M., Kmec, J., Spišák, E., & Kučerka, D. (2015). Usage of Neural Network to Predict Aluminium Oxide Layer Thickness. The Scientific World Journal, 2015, pp. 1-10.
17. Kumar, M., & Yadav, N. (2011). Multilayer perceptrons and radial basis function neural network methods for the solution of differential equations: A survey. Computers & Mathematics with Applications, 62(10), pp. 3796-3811.
18. Piasecki, A., Jurasz, J., & Marszelewski, W. (2016). Application of Multilayer Perceptron Artificial Neural Networks to Mid-Term Water Consumption Forecasting - A Case Study. Ochrona Srodowiska, 38(2), pp. 17-22.
19. Pazouki, M., Wu, Z., Yang, Z., & Moeller, D. P. F. (2015). An Efficient Learning Method for RBF Neural Networks. In Proceedings of the International Joint Conference on Neural Networks. Killarney, Ireland. pp. 1-6.
20. CZ NACE, 2016. CZ NACE – F Stavebnictví. [F Construction]. [online]. [accessed: 2016-10-10]. Available from: http://www.nace.cz/nace/f-stavebnictvi/

Стаття надійшла до редакції 29.10.16.