Usage of Multiple Perceptron Neural Networks in Determination of the Financial Plan

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Abstract

Financial planning within a company represents one of the basic activities of a company as well as a very demanding activity of the financial manager. Based on the main principles of economy and data from the previous periods (especially main financial statements – balance sheet, profit and loss, cash-flow statement) the future development of the given company is predicted. Different mathematical and statistical models and methods including statistical, causal and intuitive methods are used to carry this out. Some models, such as artificial neural networks, represent a very efficient method for prediction. The article identifies company revenues as the initial indicator in setting a company´s financial plan. Multilayer perceptron neural networks are very often used for their prediction. Information on Hornbach Company´s Profit and Loss Statement from the period of 1999 to 2015 is used as input data. A total of 1000 artificial neural networks is generated, out of which 5 most appropriate are maintained. Sensitivity analysis is also carried out. The contribution finally states that in practice, the suggested neural structures are useful for compiling a company financial plan which is always derived from the amount of sales.

Keywords: multiple perceptron neural networks, financial plan, sales prediction, neural structure, model

Introduction

Financial markets around the world have become increasingly interconnected. Financial globalization has brought considerable benefits to national economies, investors and savers, but it has also changed the structure of markets, creating new risks and challenges for market participants. Not only the effects of globalization in the financial and insurance markets are at the centre of researcher’s interest (Ceniga and Šukalová 2011), but also new methods and solutions to new conditions are being considered.

Methods of preparation of financial plan

A financial plan is „a comprehensive evaluation of an individual's current pay and future financial state by using current known variables to predict future income, asset values and withdrawal plans (Investopedia, 2016). In business, a financial plan can refer to the three primary financial statements - balance sheet, income statement, and cash flow statement. These three constitute a business plan (Homolka and Fábera 2013).

According to Mulačová (2012) financial plan can also refer to an annual projection of income and expenses for a company, division or department, and it can also contain pro forma and prospective statements. "Prospective financial statements are of two types-forecasts and projections. Forecasts are based on management's expected financial position, results of operations, and cash flows" (Rittenberg, Johnstone and Gramling 2012).

Though the term ´financial plan´ is widely used, what precisely a financial plan is, can be a little bit confusing, especially in industry. For example, the Standards of Professional Conduct (CFA 2014) publication explains the process of financial planning, but does not contain the term ´financial plan´. It implies that there are no specific templates for a financial plan and the plan is often prepared with regard to specific needs of the company or clients, using many variables such as current net worth, tax liabilities, asset allocation or estate plans.

Construction of multiple perceptron networks

Comparability and mathematical aspects of the indicators of financial analysis in the evaluation of the company enable various approaches and mathematical and statistical solutions (Vojteková and Bartošová 2009; Gazdíková and Šusteková 2009). Some of them, such as Artificial Neural Networks, offer solutions to very complex models enhanced by artificial intelligence principles (Klieštik 2013).

Artificial Neural Networks (ANN) are computation models inspired by biological neural networks, particularly by the behaviour of neurons, to approximate functions that are unknown in model populations and environments that constantly change (Dvořáková and Vochozka 2015).

The most commonly used ANN class is the multilayer perception (MLP). In MLPs and other types of ANNs, simple processing units called nodes (which simulate neurons) are linked via weighted interconnections. The interconnection weights function as multipliers that simulate the connection strengths between neurons. The nodes are commonly arranged in three or more layers. An input layer accepts the values of the predictor variables presented to the network (e.g. clinical variables, financial variables, levels of service) while one or more output nodes represent(s) the predicted output(s) (e.g. prediction of treatment outcome, business performance, quality degree). One or more hidden layers of node link(s) the input and the output layers (Michal et al 2015).

A multilayer perceptron (MLP) is a feedforward artificial neural network model which is more powerful than the single-layer model. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network. MLP is a modification of the standard linear perceptron and can distinguish data that are not linearly separable.

Since the financial plan consists of various financial statements, the forecasting process can be divided to prediction of various figures, such as costs forecasting or demand forecasting (Kliieštik and Majerová 2015). Fildes et al. (2008) aimed at forecasting and operational research and they successfully examined computationally intensive methods and applications in operations and marketing. Multilayer networks were successfully applied in cost prediction by many researchers (Huang, Xue and Dong 2015; Nagaraj and Selladurai 2003; Lin and Chang 2002; Wang, Stockton and Baguley 2010). Cost prediction is very important, but the factors of influencing cost are many and complex and the factors affect each other. Thus enterprise cost is difficult to be predicted correctly.

Neural networks were also successfully used for forecasting of chain supply (see Chen, Wee and Hsieh 2009), production and inventory management (Wang 2005; Liiv 2006; Doganis, Aggelogiannaki and Sarimveis 2008; Mansur and Kuncoro 2012) and demand (Kourentzes 2013). Neural network models were found the most efficient as compared to traditional method of forecasting.

Zhang, Cao and Schniederjans (2004) used Neural Networks models to forecast earnings per share models. They compared four types of models: univariate-linear, multivariate-linear, univariate-neural network, and multivariate-neural network using a sample of 283 firms spanning 41 industries. The proved that the neural network model was accurate than linear forecasting models and pointed out limitations of the forecasting capacity of investors in the security market.

Financial planning within a company represents one of the most demanding activities of a financial manager. Based on the data from the previous period and knowing the basic principles of economy predicts the future development of a very difficult organism, such as a company definitely is (Stehel and Vochozka 2016).

In general, I use three methods to set a financial plan. It is statistical, causal and intuitive methods (Vochozka, Rowland and Vrbka 2016). Statistical methods determine the future values of individual items of a financial plan based on time series. Causal methods suppose that the financial manager will observe changes of economical, legislative and other external environment of an enterprise, and based on these they will revise the results of previous methods so that they respond to the assumed development. Intuitive methods are based on knowledge and experience of the predictor who, without justifying it into detail, guesses the enterprise´s future development. In all three cases, we are simplifying hundreds and thousands of factors influencing the company´s life to a much lower amount, and from this simplified reality we derive the company´s future development.

Quite correctly it may be assumed that a financial manager will use all three methods compiling a financial plan. First, they will predict the basic variables of a financial plan through statistical methods. Company revenues are, indisputably such a variable, we may derive the rest of the financial plan values from them by the causal method. Subsequently, we will fit them within a certain logical frame.

The aim of this contribution is to find a suitable multilayer perceptron network useful for prediction of a company´s revenues as the initial indicator during a financial plan compilation based on an example of a specific enterprise.

Materials and Methods

The activity of an enterprise is defined briefly as an input exchange (production factors) into outputs (products). Business theory defines as production factors management work, dispositive work, material and fixed assets (Wöhe a Kislingerová 2007). The output defining the performance of an enterprise is revenue. Revenues are the basic building block on which the enterprise builds its entire financial plan.

The Hornbach corporation that deals with sale of handy-men goods, gardening goods and house-work goods, will be our model enterprise. Thus, we will be looking for the dependence of a business enterprise revenues on production factors, respectively their use. Profit and Loss Sheets from the years of 1999 to 2015 are available, thus 17 records at each Profit and Loss Statement item. To fulfil the aim of this contribution, we will be interested mainly in the following items of Profit and Loss Sheet:

1. Revenues for the sale of goods,
2. Costs on Sold Goods,
3. Personal Costs,
4. Depreciation of Long-term Fixed and Intangible Assets.

Personal costs include management wages but also the wages of executive workers. Moreover, we have included social and health insurance, which is, in a way, an income tax. Long-term Asset Depreciations express a share of long-term assets which was used up in the given economic year, and thus it must reflect in the economic result of an ordinary year.

To prepare a data file MS Excel will be used. The Statistica Programme in versions 7 and 12 by the DELL Company will be used to carry out the calculations. Subsequently it will be processed with the help of automated neural networks. We are looking for an artificial neural network (three-layer of four-layer perceptron neural network) which will be able to predict the future development of revenues for the sold goods of a business enterprise operating in the Czech Republic. All variables used are continuous.

The data will be divided into three groups:

- Training: 70 %,
- Testing: 15 %,
- Validational: 15 %.

The seed for a random choice has been determined at the value of 1,000. Down-sampling will be run randomly.

Consequently, 1,000 random artificial neural structures will be generated out of which 5 most suitable results will be retained.[1]

Activating functions in the hidden and output neuron layer will be:

1. Linear function:

$$y = k * x * w \tag{1}$$

where:

y	means output,
k	transmitting function,
x	input,
w	synaptic weight.

2. Step function:

$$S(t) = \begin{cases} 1 & ; \ t \geq 0 \\ 0 & ; \ t < 0 \end{cases} \tag{2}$$

where:

t	means time.

3. Saturating linear function:

$$S(t) = \begin{cases} 1 & ; \quad t > 1 \\ t & ; -1 \leq t \leq 1 \\ -1 & ; \quad t < -1 \end{cases} \tag{3}$$

4. Sigmoid function:

$$S(t) = \frac{1}{1 + e^{-t}} \tag{4}$$

5. Hyperbolic tangent function:

$$S(t) = \frac{1 - e^{-t}}{1 + e^{-1}} \tag{5}$$

Other setting will be default. Subsequently, sensitivity analysis will be carried out. Thus, we will define how individual manufacturing factors influence the company´s ability to generate revenues for own product and service sale.

Results and Discussion

Having applied the contribution methodology we are gaining the best five generated neural networks. Their list is given in Table No. 1.

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[1] That will be determined through the smallest squares´ method. If the differences between newly generated networks will not be significant, the training will be finished.

Tab. No. 1: Generated and Retained Neural Structures

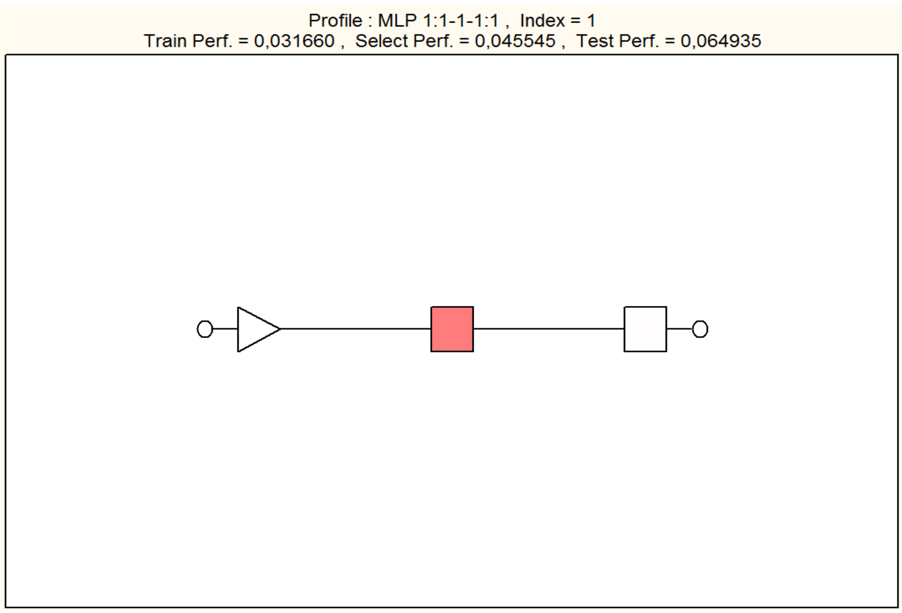
Index	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Training/ Members	Inputs	Hidden (1)	Hidden (2)
1	MLP 1:1-1-1:1	0,031660	0,045545	0,064935	0,012026	0,010140	0,016830	BP100,CG 20,CG0b	1	1	0
2	MLP 1:1-2-1:1	0,049389	0,045536	0,082864	0,016738	0,009803	0,021813	BP100,CG 20,CG2b	1	2	0
3	MLP 1:1-1-2-1:1	0,062101	0,042136	0,106837	0,020204	0,009424	0,027445	BP100,CG 20,CG7b	1	1	2
4	MLP 1:1-1-3-1:1	0,053437	0,042817	0,097727	0,017672	0,009390	0,025138	BP100,CG 20,CG4b	1	1	3
5	MLP 2:2-10-1:1	0,095757	0,008098	0,184332	0,031129	0,001749	0,053612	BP100,CG 20,CG7b	2	10	0

Source: Author

It is neural structures composed of three or four layers: input layers, the first hidden layers, possible second hidden layers and output neuron layers. The first two and the fifth neural networks are three-layer perceptron networks. The third and fourth structure is a four-layer perceptron network. The first four networks work with only one input variable.

The scheme of network no. 1, i.e. MLP 1:1-1-1:1 is denoted in Picture No. 1. It is clear that the network uses only one of three input variables. Specifically, it is the costs on sold goods, and personal costs.

Pic. No. 1: MLP 1:1-4-1:1 Scheme

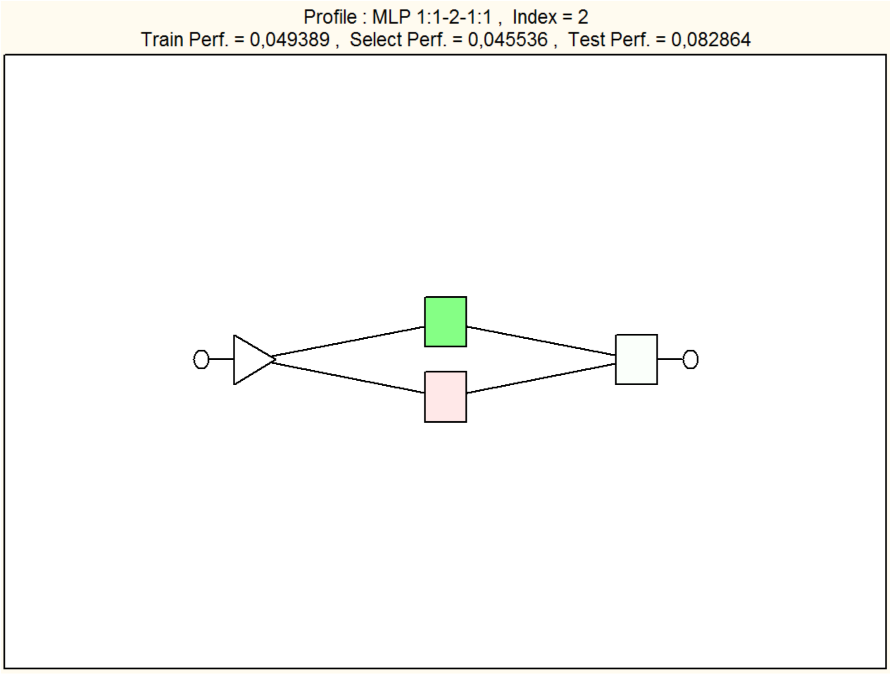


Source: Author

The network uses only one neuron in the hidden layer. Thus it is clear that the structure guesses a straight dependence between sold goods and the costs on sold goods. The enterprise would, in such case, prove a minimum of fixed assets.

The scheme of the second generated and retained network is the object of Picture No.2.

Pic. No. 2: MLP 1:1-2-1:1 Scheme

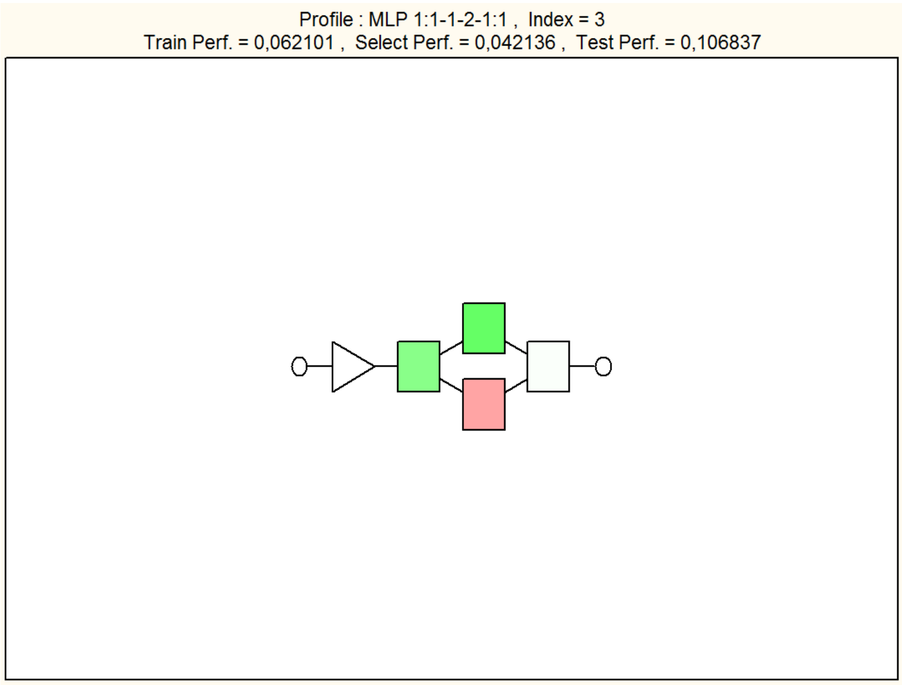


Source: Author

MLP 1:1-2-1:1 uses also one manufacturing factor – costs on sold goods. Compared to the network No. 1 it has two neurons in the hidden layer.

The scheme of the third retained MLP neural network is depicted in picture No.3.

Pic. No. 3. MLP 1:1-1-2-1:1 Scheme

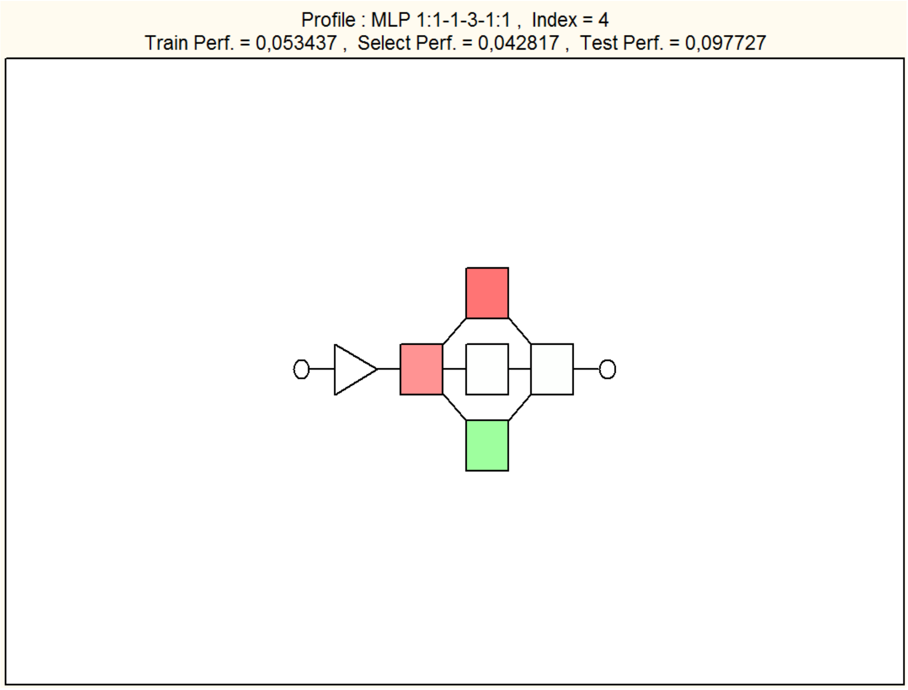


Source: Author

In this case it is a four-layer perceptron network which has one neuron in the first, hidden layer, in the second hidden layer it has two neurons. But, again it uses the only manufacturing factor – costs on sold goods.

Fourth, the MLP 1:1-1-3-1:1 network was generated. Its scheme is denoted in Picture No. 4.

Pic. No. 4: MLP 1:1-1-3-1:1 Scheme

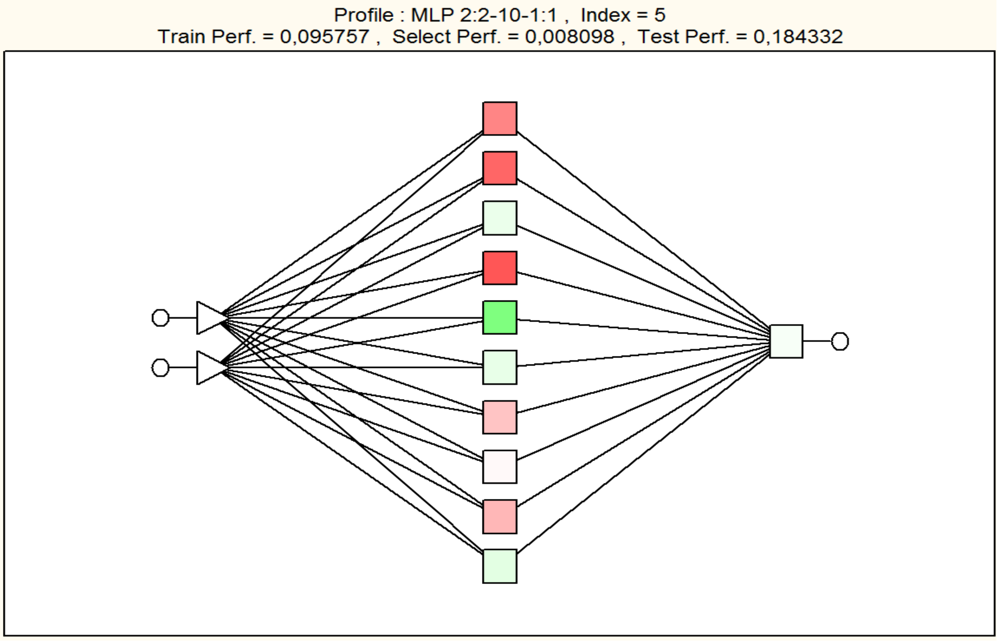


Source: Author

The four-layer perceptron network uses again one manufacturing factor – costs on sold goods. In the first hidden layer there is one neuron situated, in the second hidden layer there are three neurons.

The scheme of the fifth generated and retained neural network is depicted in Picture No. 5.

Pic. No. 5: MLP 2:2-10-1:1 Scheme



Source: Author

Three-layer perceptron network uses, besides costs on sold goods, also the depreciation of long-term assets.

In fact, it is impossible to deduce which of the generated networks offers the highest performance. Always, it is necessary to judge the training, evaluating and validational data set. If we do this also in this case, it is impossible to choose the most suitable network with certainty. Differences between them are in no way significant and thus, all generated and retained networks appear to be suitable for prediction of revenues. To illustrate this fact clearer, Table No. 2 is inserted.

Tab. No. 2:Predicted Revenues for the Sale of Goods

Year	Revenues for Sale of Goods	Revenues for Sale of Goods 1	Revenues for Sale of Goods 2	Revenues for Sale of Goods 3	Revenues for Sale of Goods 4	Revenues for Sale of Goods 5
1998	83757	122342	-17517	-14274	48602	-82267
1999	808224	798194	731043	666492	721494	752830
2001	2071204	2093514	2111236	2059710	2079557	2060963
2004	3391570	3569323	3612563	3631455	3623793	3514715
2006	3891625	3952558	3991291	4014722	4006266	4053053
2007	4461412	4524297	4548199	4558225	4553813	4717636
2008	5040467	5054933	5056613	5028740	5033096	5220847
2012	4980238	4927769	4935504	4919107	4920969	4672983
2013	4787998	4841803	4853371	4843863	4844173	4612308
2015	5096173	5113031	5111794	5078160	5083733	4976125
2016	5554350	5543607	5517834	5431210	5447129	5650056

Note: Values are given in thousands of CZK.

Source: Author

Using the table it is possible to compare the real amount of revenues for sale of goods in individual years with the prediction according to individual retained neural networks. Based on the residues we will thus guess the possible absolute error in partial years. At the first sight it is obvious that not even in a table the prediction of future revenue development we will be able to find any significant differences between individual networks and thus we may state that all generated and retained neural networks seem to be useful in practice.

Nevertheless, interesting results are provided by sensitivity analysis. Its results are given in Tab. No. 3.

Tab. No. 3. Sensitivity Analysis

Data Set	Costs on Sold Goods	Depreciation of Long-term Fixed and Intangible Assets
T.Ratio.1	27,0313	
T.Rank.1	1,0000	
S.Ratio.1	22,7269	
S.Rank.1	1,0000	
X.Ratio.1	15,7151	
X.Rank.1	1,0000	
T.Ratio.2	19,4248	
T.Rank.2	1,0000	
S.Ratio.2	23,2347	
S.Rank.2	1,0000	
X.Ratio.2	12,2156	
X.Rank.2	1,0000	
T.Ratio.3	16,0975	
T.Rank.3	1,0000	
S.Ratio.3	24,0430	
S.Rank.3	1,0000	
X.Ratio.3	9,7461	
X.Rank.3	1,0000	
T.Ratio.4	18,4016	
T.Rank.4	1,0000	
S.Ratio.4	24,1788	
S.Rank.4	1,0000	
X.Ratio.4	10,6244	
X.Rank.4	1,0000	
T.Ratio.5	14,3966	3,12024
T.Rank.5	1,0000	2,00000
S.Ratio.5	157,9418	35,70914
S.Rank.5	1,0000	2,00000
X.Ratio.5	5,3997	1,21572
X.Rank.5	1,0000	2,00000

Note: T stands for the testing set of data, S stands for the sentinel set and X stands for validation set of data.

Source: Author

The analysis always calculates the weight and order of importance between input variables, in all input variables. Out of three input variables the models chose, in four cases, only one input variable, i.e. costs on sold goods, in the fifth case it also included depreciation of long-term assets. The sensitivity analysis thus contains 18 data sets. It may be concluded that revenues for sold goods are in the case of Hornbach corporation determined as costs on sold goods. Other manufacturing factors do not play a significant role. The result may be understood as very positive for the corporation. In case only straight costs are created it may influence its economy result much easier. It may apply a suitable cost policy and thus increase possible revenues. The result is to a certain extent also a commitment for the management how to retain personal costs and depreciations on the same level.

Conclusion

The aim of this contribution was to find a suitable multi-layer perceptron network useful for predicting enterprise revenues as an initial indicator compiling a financial plan on an example of a specific enterprise.

The aim of this contribution has been fulfilled. Five best neural structures have been generated and retained. Among the predicted values of individual networks significant differences have not been identified. All generated networks are useful for an evaluated enterprise. Sensitivity analysis has subsequently proved that future revenues may be estimated as a base of sold-goods costs. Only in the case of the fifth generated network long-term asset depreciations were used. They do not have to be used in the application necessarily. Their significance is comparatively small. They take almost 18.6% in Model No.5.

The suggested neural structures are useful in practice for an enterprise financial plan composition (it has been proved in case of Hornbach Corporation) which is always derived from revenue amount. Nevertheless, the truth is that the suggested model always assumes that demand for the company´s products is not limited. Further, it is assumed that only manufacturing capacity may be limited in this case. The financial manager will then follow the revenue estimation with the application of causal methods and subsequently of intuitive methods.

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