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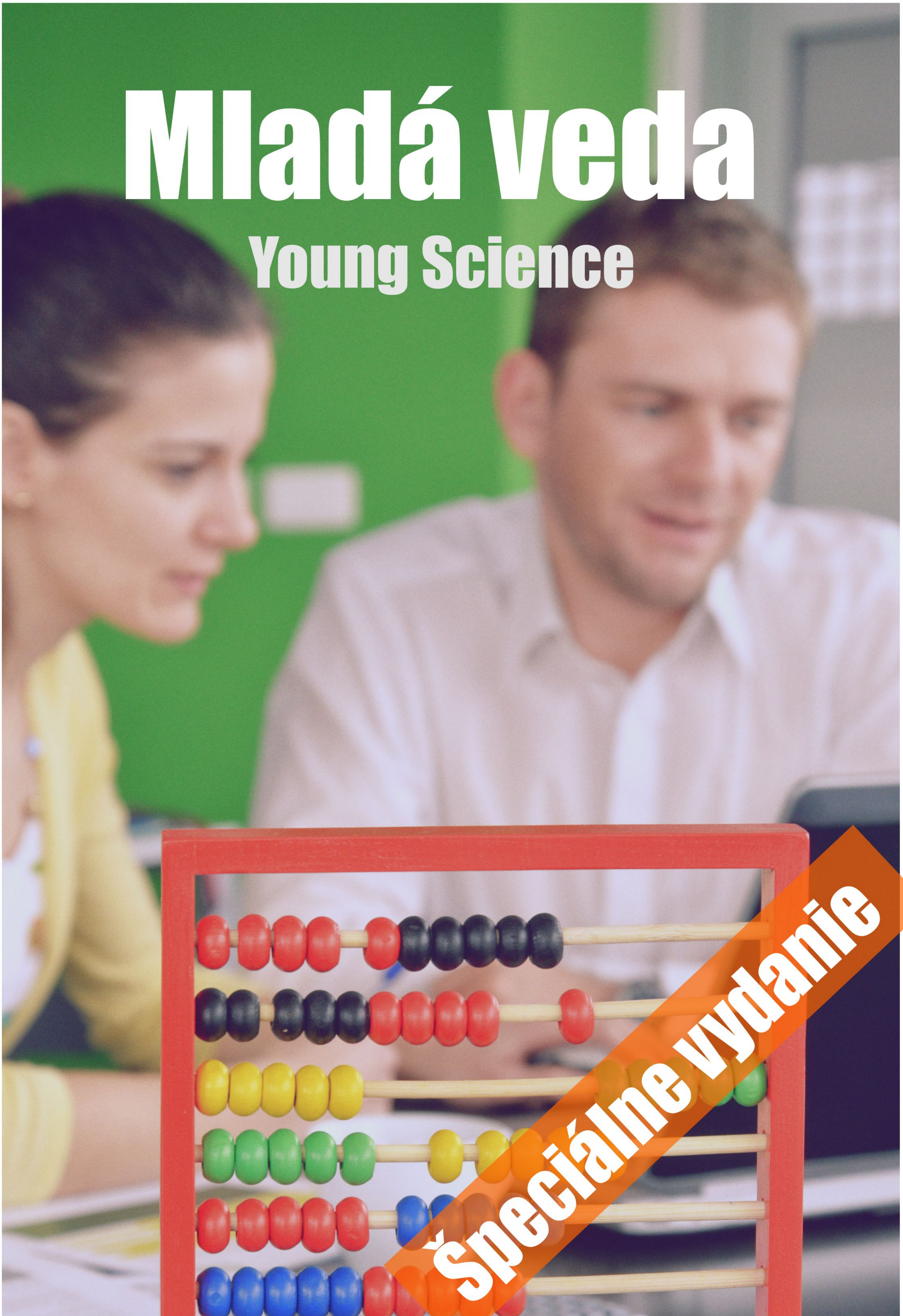

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STANOVENIE FINANČNÉHO PLÁNU KONKRÉTNEJ SPOLOČNOSTI POMOCOU NEURÓNOVEJ SIETE ZÁKLADNÉ RADIÁLNE FUNKCIE

DETERMINING THE FINANCIAL PLAN OF A CONCRETE COMPANY USING THE RADIAL BASIC FUNCTION NEURAL NETWORK

Marek Vochozka[1]

Autor pôsobí ako rektor na Vysokej škole technickej a ekonomickej v Českých Budějoviciach. Vo svojom výskume sa venuje najmä témam ako sú: Metódy komplexného hodnotenia podniku, umelé neurónové siete, finančná analýza a predikcia budúceho vývoja spoločnosti.

Author is a rector of Institute of Technology and Business in Ceske Budejovice. His research focuses mainly on topics such as: methods for comprehensive evaluation of the company, artificial neural networks, financial analysis and prediction of the future development of the company.

Abstract

A financial plan has a crucial influence on way of funding and investing funds, on competition strategy and on complete business success. Nowadays there are three main methods of financial planning – intuitive, statistical and causal. As each method, also these three methods have some advantages and disadvantages. Currently is the most optimal causal method, but in the past, the intuitive method was in the forefront. Presently other methods of financial planning for companies are developing, for example the artificial neural networks. This contribution describes the radial basic function neural network. The aim is to find suitable radial basic function neural networks for predicting the future development of sales from goods sold. 1000 random neural networks are generated and the top five of which are retained. The proposed neural structures are used in practice when compiling the financial plan of the company.

Key words: financial plan, radial basic function, artificial neural network, financial statements

Abstrakt

Finančný plán má zásadný vplyv na spôsob financovania investovania finančných

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prostriedkov, na stratégiu hospodárskej súťaže a kompletný podnikový úspech. Dnes existujú tri hlavné metódy finančného plánovania – intuitívne, štatistické a kauzálne. Ako každá metóda, tak aj tieto tri majú svoje výhody a nevýhody. V súčasnosti je najoptimálnejšia kauzálna metóda, v minulosťou bola v popredí metóda intuitívna. V súčasnosti sa pre firmy vyvíjajú aj iné metódy finančného plánovania, napríklad umelé neurónové siete. Tento príspevok popisuje radiálnu základnú funkciu umelej neurónovej siete. Cieľom je nájsť vhodnú radiálnu základnú funkciu neurónových sieti pre predikciu budúceho vývoja tržieb za predaný tovar. Je generovaných 1000 náhodných neurónových sietí, z nich 5 najvhodnejších je zachovaných. Navrhované neurónové štruktúry sa používajú v praxi pri zostavovaní finančného plánu spoločnosti.
Kľúčové slová: finančný plán, radiálne základné funkcie, umelé neurónové siete, finančné výkazy

Introduction

According to Gazdíková and Šusteková (2009) financial planning is deciding on a way of funding (obtaining capital sources) and investing funds into company property. The compilation of such a plan has a crucial influence on competition strategy (Vrchota, 2013). It is the key to business success. The output of the plan is financial statements. These are the planning balance sheet, profit and loss sheet and cash flow plan sheet (Stehel and Vochozka, 2016). They are compiled for the whole planned period and are elaborated in individual accounting periods and expanded even further in individual months (Vochozka et al., 2016).

Nowadays there are three main methods of financial planning: intuitive, statistical and causal (Vojteková and Bartošová, 2009). The intuitive method is based only on the experience and subjective estimates of the person creating the financial plan. The disadvantages are simplification and a high probability of omitting significant mutual relations (Gansel, 2008).

The statistical method extends time series in the future (this especially includes regression analysis, proportional property growth or liabilities growth). The disadvantage is an unrealistic presumption that past developing economic variables will stay the same in the future (Baldacci et al., 2009).

In the causal method, input data are based on the information about current company property and current economy results, on the output and other economic plans. The source is the prediction of the development of macroeconomic indicators (Li, 2013). The causal method is the most optimal possible method. Others include discriminant analyses, regression analyses, time series methods and Artificial Neural Networks (ANNs).

In the past, the intuitive method was in the forefront. Presently other methods of financial planning and predictions for companies are developing, for example the ANNs. According to Dvořáková and Vochozka (2015) ANNs are computation models inspired by biological neural networks. Slavici et al. (2012) claim, that ANNs' task is to replace human thinking, which doesn't always have the ability to take in and interpret a huge amount of information. ANNs with an excellent non-linear approximation ability quickly developed, and since the 1980s are being widely used in non-linear fields (Michal et al., 2015). There are many types of ANNs. The question is which model could be suitable for determining the financial plan of a company. A possibility seems to be the Radial Basic Function (RBF)

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neural network. According to Pazouki et al. (2015) traditionally, a RBF neural network can be thought of as a two-layer feed forward network, which is used for function approximation and time-series forecasting, for classification or clustering tasks (interpolation, chaotic time-series modelling, speech recognition, image restoration, 3D object modelling, data fusion, etc.). Guan et al. (2016) claim that the number of neurons in the hidden layer of the RBF neural network is difficult to determine. In general, we need to test several times according to experience and prior knowledge, which lacks a strict design procedure on a theoretical basis. Besides, we don't know whether the RBF neural network is convergent.

The method of the topology of the RBF neural network is simple, but its generalization ability is strong (Jingfei et al., 2016). It demonstrates a good classification and approximation performance in application (Bartool et al., 2013). The RBF neural network can be trained extremely quickly and the training of a RBF doesn't suffer from a local minimum (Lou and Kuang, 2005). The topology of the RBF neural network comprises of an input layer, a hidden layer and an output layer formed by linear processing units (Gubana, 2015). According to Hashemi and Aghamohammadi, (2013) the basic idea of this neural network is to transform the input data into high dimensional space.

When designing the RBF neural network, the main parameters which are necessary to determine are as follow: the number of nodes in the hidden layer; the center and width of the hidden layer nodes which we can write out, the formula; the weights between the hidden layer to the output layer and the offset of the output layer, the subtraction cluster, etc. (Wang and Huang, 2015, p. 2). RBF act on the input patterns, and then send the outcomes to the output neuron in the output layer. Thereafter, the output neuron as the final outcome of the network is a weighted sum of the hidden neuron patterns. Generally, a RBF neural network is a multivariate function $\Phi: \mathbb{R}^S \rightarrow \mathbb{R}$, such that (Pazouki et al, 2015, 1):

$$\Phi(x, x^C) = \emptyset(\| x - x^C \|) \tag{1}$$

Where $\emptyset: [0, \infty) \rightarrow \mathbb{R}$ is an univariate function (often taken to be the Gaussian function), xC is the center point of the RBF, the norm $\| \cdot \|$ is typically the Euclidean distance, and S is the dimension of the input patterns.

The RBF neural network has been applied in a wide variety of fields. It proposes a peak density function to determine the number of neurons in the hidden layer. In contrast to existing approaches, the centres and the widths of the radial basis function are initialized by extracting the features of samples. So the uncertainty caused by a random number when initializing the training parameters and the topology of the RBF neural network is eliminated. The convergence rate and approximation precision of the RBF neural network are improved significantly (Guan et al., 2016, p. 485). Lou and Kuang (2005) applied RBF neural networks to enterprise credit comprehensive evaluation. The results show that the RBF neural network model possesses the highest precision and best generalization ability under fewer samples than other traditional methods. Its predictive accuracy and adaptability was also confirmed by Hou et al. (2003), Hashemi and Aghamohammadi (2013), Wang and Huang (2015), Guan et al. (2016) and others.

The aim of this article is to find suitable RBF neural networks for predicting sales on the example of a particular company.

Methodics

Generally, we can define the activities of a company as the conversion of production factors to products. The economic theory proposes labor, land and capital as production factors. Some economists additionally include know-how, or even money, among factors of production. However, these factors are not entirely appropriately defined for the practice of enterprise economy. Therefore, for example Wöhe and Kislingerová (2007) determined the factors of production to be management work, dispositive work, material and fixed assets. It is thus possible to work with production factors at company level and infer a correlation between production factors as inputs and company sales as outputs. Moreover, sales are fundamental building blocks on which the company builds its entire financial plan.

Our model company will be the firm Hornbach, which sells DIY merchandise and products for garden and house work.

We will therefore search for the dependence of sales of a commercial enterprise on production factors, or the expenditure of which. Profit and loss statements for the years 1999-2015 are available, a total of 17 entries for each item of a profit and loss account.

For the purpose of fulfilling the objectives of the article, we will be interested in these profit and loss entries:

1. Sales of goods,
2. The cost of goods sold,
3. Personnel expenses,
4. Depreciation of tangible and intangible fixed assets.

Personnel expenses include the salaries of both management and executives. In addition, we incorporated social and health insurance, which is in its way income tax. The depreciation of fixed assets expresses the share of fixed assets consumed in a given marketing year, and therefore must be reflected in the profit or loss of the current year.

For the preparation of the data file, MS Excel will be used. DELL software Statistica, versions 7 and 12, will be used for calculation. This will then be processed by automated neural networks. We are looking for an artificial neural network capable of predicting the future development of revenues from goods sold by a business enterprise operating in the Czech Republic.

All used variables are continuous. The data will be divided into three groups: Training (70%), Testing (15%), Validating (15%). The seed for random selection was set to a value of 1000. Subsampling will take place randomly. Subsequently, 1000 artificial neural structures will be generated, from which we will retain 5 most appropriate results[2].

[2] This is determined using the method of least squares. When differences between newly generated networks stop being substantial, training will be terminated.

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The activation functions for the hidden and output layers of neurons will be the linear and the logistic function. Other settings will stay default.

Subsequently, a sensitivity analysis will be performed, from which we will determine how individual production factors affect the company's ability to generate revenues from sales of own products and services.

Results and Discussion

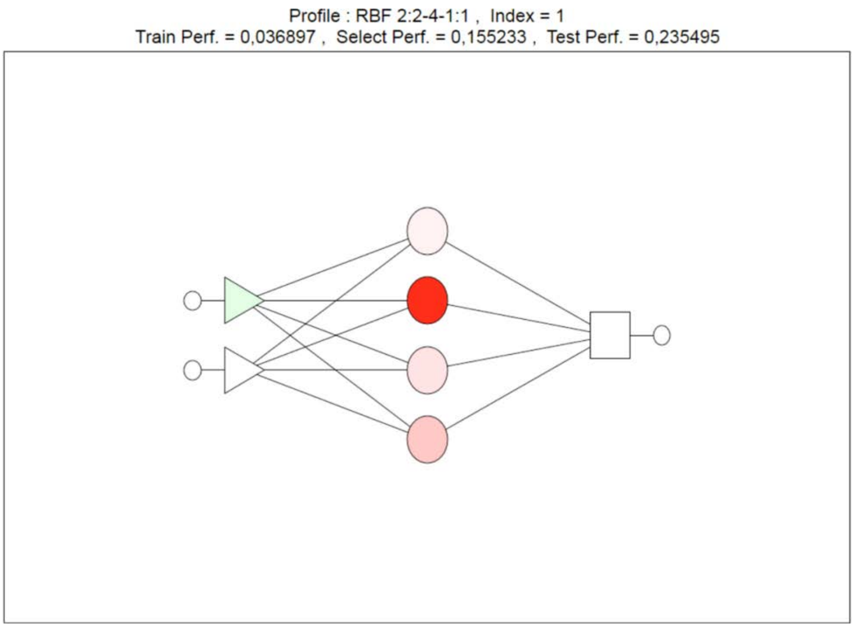
We have obtained the five best neuron networks by generation as described in the methodics of the study. They are listed in the table numbered 1.

Index	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error
1	RBF 2:2-4-1:1	0.036897	0.155233	0.235495	0	0
2	RBF 3:3-3-1:1	0.096987	0.049225	0.272203	0	0
3	RBF 3:3-5-1:1	0.046234	0.119551	0.222529	0	0
4	RBF 3:3-4-1:1	0.091352	0.079881	0.261555	0	0
5	RBF 1:1-4-1:1	0.030387	0.019384	0.035051	0	0
Index	**Profile**	**Test Error**	**Training/ Members**	**Inputs**	**Hidden (1)**	**Hidden (2)**
1	RBF 2:2-4-1:1	0	KM,KN,PI	2	4	0
2	RBF 3:3-3-1:1	0	KM,KN,PI	3	3	0
3	RBF 3:3-5-1:1	0	KM,KN,PI	3	5	0
4	RBF 3:3-4-1:1	0	KM,KN,PI	3	4	0
5	RBF 1:1-4-1:1	0	KM,KN,PI	1	4	0

Table1 – Generated and preserved neuron structures
Source: Own

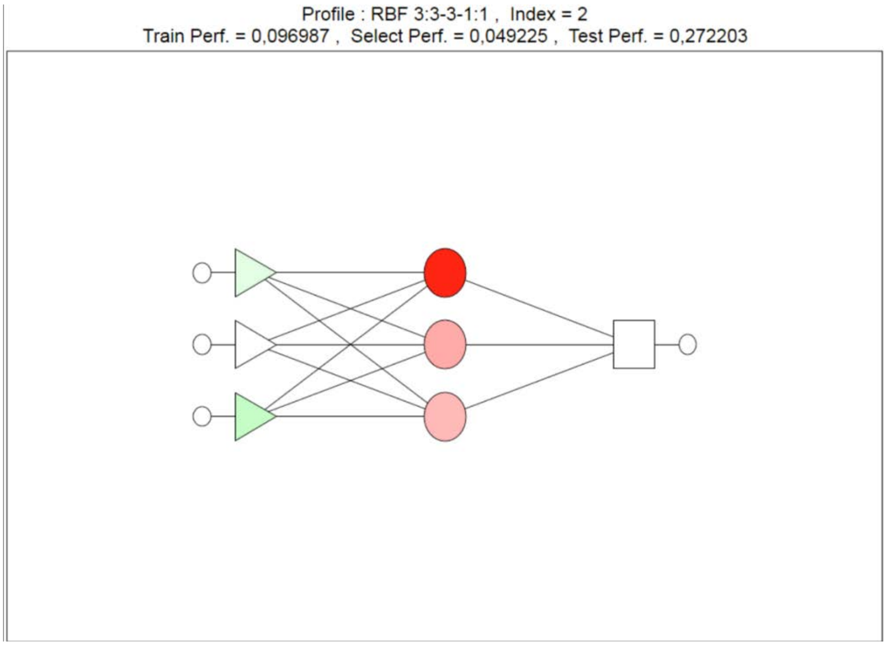
The neural structures are composed of three layers: the input layer, hidden layer and output layer of neurons. The first neural network works with two entrances. The second, third and fourth, work with all factors of production. The fifth, on the contrary, assumes the use of a single factor of production for prediction.

Network diagram number one, is RBF 2:2-4-1:1, is shown in the picture one. It is apparent from the diagram that the network utilizes only two of the three input variables. Specifically, the cost of goods sold and personnel costs.



Picture 1 – Scheme RBF 2:2-4-1:1
Source: Own

The network uses 4 neurons in the hidden layer. The scheme of the second generated and preserved network is the subject of picture 2.



Picture 2 – Scheme RBF 3:3-3-1:1
Source: Own

RBF 3:3-5-1:1 makes use of all the factors of production. Just like network number one, it works with the cost of goods sold and personnel costs. It additionally includes the depreciation of fixed assets.

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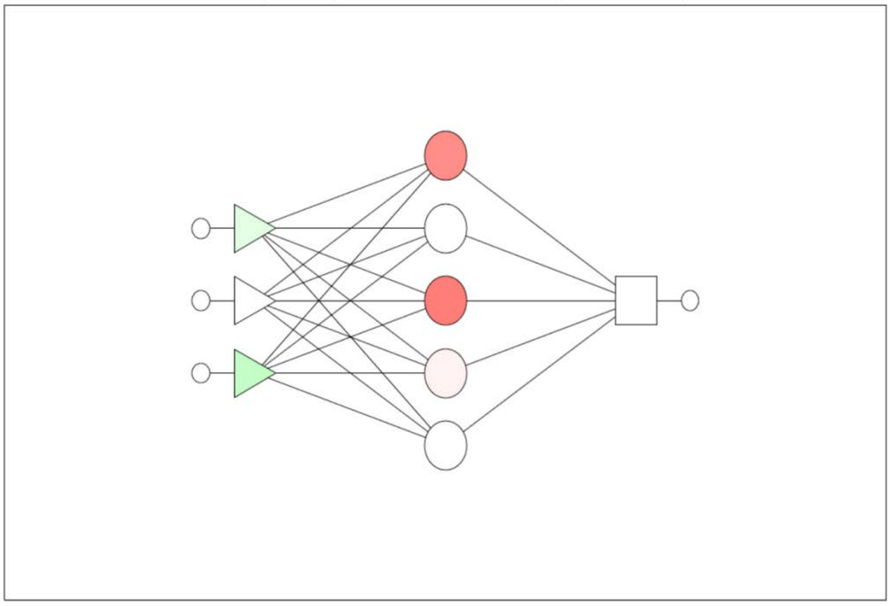
The scheme of the third preserved RBF neural network is shown in picture 3.



Picture 3 – Scheme RBF 3:3-5-1:1
Source: Own

The fourth (RBF 3:3-4-1:1) and fifth neural network (RBF 1:1-4-1:1) were similarly generated and preserved.

It is basically impossible to infer which generated network offers the highest performance. It is always necessary to assess the training, verifying and validating data set. If we do so in this case, the most appropriate network cannot be confidently selected. The differences between them are not particularly significant, and thus all generated and preserved networks appear appropriate for sale predictions.
Table number two is inserted for better illustration.

	Revenues from sale of goods	**Revenues from sale of goods.1**	**Revenues from sale of goods.2**	**Revenues from sale of goods.3**	**Revenues from sale of goods.4**	**Revenues from sale of goods.5**
1999	808224	841864	808951	812616	850306	819644
2000	1523406	1449736	1627517	1536939	1529898	1498184
2001	2071204	2084642	2069274	2089839	2079014	2076427
2002	2071204	2084642	2069274	2089839	2079014	2076427
2004	3391570	3456294	3292643	3319467	3319973	3441225
2006	3891625	3857328	3716785	3816192	3752362	3852236
2011	4664167	4584094	4729909	4802142	4719076	4569551

2012	4980238	4928638	5066390	4861085	5064481	4962555
2013	4787998	4865370	5037842	4845597	5030708	4868548
2015	5096173	5182589	5211719	5174936	5207941	5155323
2016	5554350	5504962	5209854	5491507	5207386	5520039

Table 2 – Predicted revenues from sale of goods
Source: Own

In the table, it is possible to compare the actual amount of revenues from the sales of goods in individual years with predictions according to the individual preserved neural networks.

Based on the residues we estimate the possible absolute error in partial years. It is immediately apparent that we cannot find any significant differences between individual networks even in the table of sales predictions, and so we can once again say that all generated and preserved neural networks appear to be usable in practice. The summary of residues of the individual generated networks is presented in table number 3.

	Residues				
	Revenues from sale of goods.1	**Revenues from sale of goods.2**	**Revenues from sale of goods.3**	**Revenues from sale of goods.4**	**Revenues from sale of goods.5**
1999	33639.8	727	4392	42082	11419.6
2000	-73670.1	104111	13533	6492	-25221.9
2001	13438	-1930	18635	7810	5222.7
2002	13438	-1930	18635	7810	5222.7
2004	64723.9	-98927	-72103	-71597	49654.8
2006	-34296.5	-174840	-75433	-139263	-39388.9
2011	-80073.1	65742	137975	54909	-94615.6
2012	-51600.1	86152	-119153	84243	-17683.2
2013	77371.8	249844	57599	242710	80550.4
2015	86416	115546	78763	111768	59150.2
2016	-49387.5	-344496	-62843	-346964	-34310.8
Total	0.2	-1	0	0	0

Table 3 – Residues of generated and preserved neural networks RBF
Source: Own

As expected, we are searching for residues that in each item, therefore each year, approach the value of 0. On the other hand, it would certainly be interesting to evaluate the entire analysed time period. For information, a sum row has been inserted into the table. Even in this situation we are looking for that optimum value which is close to zero. In our case the ideal values are reached by networks 3, 4 and 5. Yet even the remaining two, namely 1 and 2, deviate minimally. Specifically, the sum of residues of the first RBF reaches the value of 0.2, in the case of the other RBF it equals -1. Considering the residue size of each network in individual years, this deviation is completely negligible. We can thus conclude that all five generated and preserved networks achieve very good results.

The sensitivity analysis provides equally interesting results. The analysis always calculates the weight and order of importance among input values for all input values. We have three input values, five preserved networks and always three files. In total, we are working with 36 variable files (two networks do not use all three input variables). We consider the cost of goods sold to be the most important variable. In the case of three networks it ranked first in order of priority, then it ranked twice in the second place. Personnel expenses were placed first twice in the notional importance ranking and ranked second twice. In the case of the fifth neural network, the target variables are not important for calculation. The depreciation of fixed assets ranked third three times, which puts it on the last rung of the importance of input parameters important for calculating revenues from goods sold. In the other two cases, they were not important for the calculation at all.

Conclusion

The aim of this paper was to find a suitable RBF neural network for predicting sales on the example of a particular company.

It could be said that the aim of the paper has been met. 1000 random neural networks were generated. Top five neural structures have been generated and retained. There have been no fundamental differences identified among the predicted values of individual networks. All generated networks are usable for the evaluated the company. The sensitivity analysis subsequently found that it is possible to estimate future revenues based primarily on the cost of goods sold and personnel costs. The depreciation of fixed assets was seen as an irrelevant variable to calculate revenue.

The proposed neural structures are practical to use when compiling a financial plan of a company, which is always derived from the amount of sales. But the truth is that the proposed model always assumes that the demand for the company's products is not limited. It is believed that the restrictions in this case can only be productive capacities.

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