Usage of Generalized Regression Neural Networks in Determination of the Enterprise's Future Sales Plan

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Abstract

Neural networks have recently been gaining popularity in the business practice. Research has even confirmed their better performance over traditional methods. This paper gives an overview of one of the types of neural networks, generalized regression neural networks. These are then used to establish a plan for the future sales of a company. However, generalized regression neural networks also have their drawbacks. They are oversized and have a long computation time. Despite these disadvantages the article searches for, based on data from the profit and loss accounts of the food company Friall, s.r.o. from the years 1995-2015, the dependence of revenues on production factors. 1000 random neural structures are generated, from which the 5 most appropriate are preserved using the method of least squares. Additionally, a sensitivity analysis is conducted to determine how the individual production factors affect the firm's ability to generate revenue. The proposed neural network is potentially applicable in practice when compiling the financial plan of a company derived from the amount of sales.

Keywords: Generalized Regression Neural Networks, enterprise's sales, production factors, neural structure

Introduction

Neural networks have already a rich history in business applications. In various areas of business, the neural networks were examined and compared against other methods of prediction (Vrchota 2013). In most cases, their performance was found to be superior though sometimes, certain negative aspects as computation time or programming experience were mentioned. The last progress in neural networks development have brought in more efficient and client-friendly models that can be more readily used in practice.

Construction of Generalized Regression Neural Networks

According to Dvořáková and Vochozka (2015) a generalized regression neural network (GRNN) is often used for function approximation. It has a radial basis layer and a special linear layer. All GRNNs have four layers (input layer, hidden layer, pattern or summation layer, and decision layer). The most significant disadvantage of GRNN models if compared to multilayer perceptron networks is their size and longer computation time during scoring since there is one neuron for each training row (Vochozka and Sheng, 2016).

The basic GRNN equation is (1):

$$Y\,(x)= \frac{\sum Y_i e^{-\left(\frac{d_i 2}{2\sigma^2}\right)}}{\sum e^{-\left(\frac{d_i 2}{2\sigma^2}\right)}} \tag{1}$$

where $d_i{}^2 = (x-x_i)^T\ (x-x_i)$, x is the input sample, x_i is the training sample, $d_i{}^2$ is the Euclidean distance from the x and x_i and it signifies how much the training sample can contribute to the output of the particular test sample. The spread constant, σ, is the only unknown parameter and it can be tuned by training process to an optimum value where the error will be very small.

As already mentioned above, the main disadvantage of GRNN (and of neural networks in general) if compared to other probabilistic methods is that it requires substantial computation time. There are several ways to overcome this disadvantage. One is to use a clustering versions of GRNN or precisely, a double clustering version (Specht, 2006) because one use of the clustering algorithm is not sufficient. According to Specht, the second clustering not only speeds up the testing but also replaces the division required for kernel regression with simply the search for the nearest neighbour.

Usage of GRNN-based models in business practice

The history of application of neural networks in business is already rather long and abundant. Since the researches have produced numerous studies, some of recent papers focus on the various approaches to application of neural networks in business. One of such researchers, namely Tkáč and Verner (2016), provides a systematic overview of neural network applications in business between 1994 and 2015 and concludes that the most of the researches has aimed at financial distress and bankruptcy problems, stock price forecasting, and decision support, with special attention to classification tasks. Neural networks were also successfully used for forecasting of chain supply (see Chen, Wee and Hsieh 2009), production and inventory management (Wang 2005) and demand (Kourentzes 2013).

Very often, neural networks have been compared against classical statistical methods. In most literatures, neural networks were found to perform better (Zhang, Cao and

Schniederjans 2004; Kourentzes 2013; Arunraj and Ahrens 2015; Mitrea, Lee and Wu 2009; Gazdíková and Šusteková 2009; Vojteková and Bartošová 2009).

Besides conventional multilayer feedforward network with gradient descent backpropagation, various hybrid networks or combinations of neural networks and other methods have been developed in order to improve the performance of standard models. Also, neural networks were used along with various data pre-processing and sorting methods (Lahmiri 2016) or, on the other hand, data provided by neural networks models were post-processed (e.g. Tsai and Chiou 2009, used data predicted by the neural network model to construct a decision tree model to generate useful decision rules for earnings management).

Lahmiri (2016) employed GRNN for training and testing patterns extracted by variational mode decomposition (VMD) and empirical mode decomposition (EMD), both of which methods have been successfully applied to adaptively decompose economic and financial time series for forecasting purpose. He compares these two GRNN-based models to feedforward neural networks and autoregressive moving average (ARMA) process and finds the VMD-GRNN models as suitable to analyse noisy data (an advantage of VDM over EMD), fast in processing and simple to implement which makes is very attractive to users.

Numerous models of future earnings and sales of a company have been suggested but most of them were not able to predict future without a significant error (Slabá 2016). As Höglund (2012) states, the reason is that most of the models used were linear ones while, as shown in several studies, the nature of future earnings is non-linear. Neural networks offer an alternative way to deal with the non-linearity. Höglund compared two models based on traditional statistical approaches and three models based on neural networks (self-organizing map, multilayer perceptron and GRNN) and found that the GNRR model performed best, being followed by the other two neural network models.

The aim of the article is to find a suitable GRNN for the prediction of sales of a company on the example of a particular enterprise.

Materials and Methods

We can generally define the activities of a company as the conversion of production factors to products. The economic theory proposes labour, land and capital as production factors (Stehel and Vochozka 2014). 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 (Vochozka, Rowland and Vrbka 2016). 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.

Our model company will be the corporation Friall, s.r.o. This is a South Bohemian food company, which (Friall 2016), "is the largest manufacturer of frozen potato products in the Czech Republic and employs an average of 100 workers. The company specializes exclusively in the production of **deep-frozen potato products**, and also offers the option of pallet storage in refrigerated chambers with a capacity of **4,000 pallet places**."

We will therefore search for the dependence of sales of a commercial enterprise on production factors, or the consumption of which. Profit and loss accounts 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 account entries:

1. Revenue from sales of own products and services,
2. Consumption of material and energy,
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, version 7, will be used for calculation. This will then be processed by an intelligent task solver.

We are looking for an artificial neural network capable of predicting the future development of revenues from own goods and services sold by a food manufacturing enterprise operating in the South Bohemian Region.

All used quantities 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 [1].

For GRNN the activation function is determined as follows:

$$e - \left(\frac{d_j^2}{2\sigma^2}\right) \qquad (2)$$

Other settings will stay default.

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

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 methods of the study. They are listed in the table numbered 1.

Table 1. Generated and preserved neuron structures

Index	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Training/ Members	Inputs	Hidden (1)	Hidden (2)
1	GRNN 3:3-11-2-1:1	0,802038	0,853132	0,932658	0,000017	0,000006	0,000015	SS	3	11	2
2	GRNN 3:3-11-2-1:1	0,803192	0,853603	0,932780	0,000017	0,000006	0,000015	SS	3	11	2
3	GRNN 3:3-11-2-1:1	0,805938	0,854734	0,933077	0,000017	0,000006	0,000015	SS	3	11	2
4	GRNN 1:1-11-2-1:1	0,921977	0,893857	0,894949	0,000019	0,000005	0,000014	SS	1	11	2
5	GRNN 2:2-11-2-1:1	0,888524	0,821596	0,898864	0,000018	0,000005	0,000014	SS	2	11	2

Source: Author

The neural structures are composed of four layers: the input layer, first hidden layer, second hidden layer and output layer of neurons. The first three generated networks accept all three production factors, which are the consumed material and energy, personnel costs and the depreciation of fixed assets, as input quantities. The fourth generated structure assumes the use of a single factor of production, the consumption of material and energy. The fifth preserved network calculates only with the consumption of material and energy and with the depreciation of fixed assets. All networks have 11 neurons in the first hidden layer, 2 neurons in the second hidden layer and 1 neuron in the output layer.

The characteristics of each variable in the individual sets of variables (i.e. training, testing, and validating) are listed in table number 2.

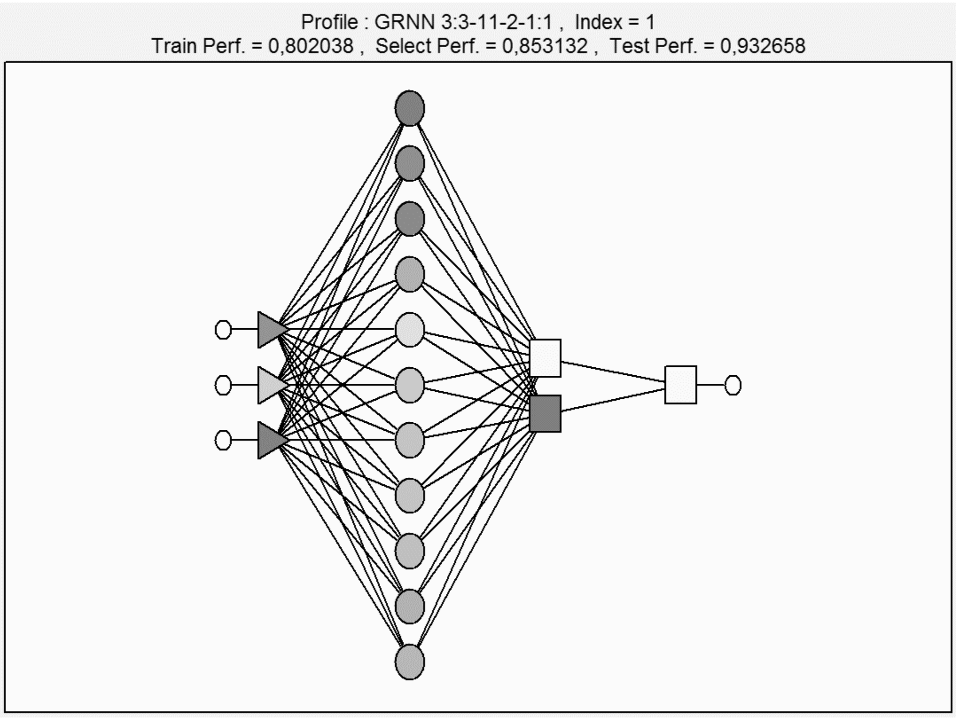
Table 2: Statistical characteristics of individual sets of data

	Data Mean	Data S.D.	Error Mean	Error S.D.	Abs E. Mean	S.D. Ratio	Correlation
T.Sales of own products and services.1	213380,0	44045,2	3283,0	35325,9	25928,8	0,8	0,9
T.Sales of own products and services.2	213380,0	44045,2	3280,1	35376,8	25950,4	0,8	0,9
T.Sales of own products and services.3	213380,0	44045,2	3272,4	35497,7	26001,7	0,8	0,9
T.Sales of own products and services.4	213380,0	44045,2	2499,4	40608,7	28013,1	0,9	0,9
T.Sales of own products and services.5	213380,0	44045,2	2148,7	39135,2	28196,2	0,9	0,9
S. Sales of own products and services.1	211405,4	12314,4	6363,9	10505,8	11013,8	0,9	0,6
S. Sales of own products and services.2	211405,4	12314,4	6347,4	10511,6	11003,2	0,9	0,6
S. Sales of own products and services.3	211405,4	12314,4	6307,8	10525,5	10977,8	0,9	0,6
S. Sales of own products and services.4	211405,4	12314,4	4056,8	11007,3	10083,6	0,9	0,7
S. Sales of own products and services.5	211405,4	12314,4	3839,3	10117,4	9497,6	0,8	0,6
X. Sales of own products and services.1	222908,2	33579,1	-2588,5	31317,9	25003,4	0,9	0,9
X. Sales of own products and services.2	222908,2	33579,1	-2612,2	31322,0	25000,5	0,9	0,9
X. Sales of own products and services.3	222908,2	33579,1	-2669,1	31331,9	24993,8	0,9	0,9
X. Sales of own products and services.4	222908,2	33579,1	-5932,7	30051,6	23526,2	0,9	0,9
X. Sales of own products and services.5	222908,2	33579,1	-6101,4	30183,1	23398,7	0,9	0,8

Note: T signifies training, S testing and X the validating data set.
Source: Author

For illustrative purposes, the scheme GRNN 3:3-11-2-1:1 is shown on figure number one, it is respectively the first generated and stored neural network.

Fig. 1: Scheme GRNN 3:3-11-2-1:1



Source: Author.

We are searching for the one of the five preserved networks that exhibits the highest performance in all three data groups, ideally a similar performance in all three and is generally the least error-prone. Network number 4, GRNN 1:1-11-2-1:1, thus looks the best optically.

It is additionally advisable to perform a sensitivity analysis and to determine the most important variable. Concrete results are given in table number 3.

Tab. 1: Analysis of sensitivity

	Material and energy consumption	Personnel costs	Depreciation of intangible and tangible fixed assets
T.Ratio.1	1,123959	1,131887	1,066473
T.Rank.1	2,000000	1,000000	3,000000
S.Ratio.1	1,093352	0,979107	1,080824
S.Rank.1	1,000000	3,000000	2,000000
X.Ratio.1	1,075594	0,988749	1,003419
X.Rank.1	1,000000	3,000000	2,000000
T.Ratio.2	1,122912	1,130728	1,065911
T.Rank.2	2,000000	1,000000	3,000000
S.Ratio.2	1,093071	0,979128	1,080692
S.Rank.2	1,000000	3,000000	2,000000
X.Ratio.2	1,075448	0,988863	1,003422
X.Rank.2	1,000000	3,000000	2,000000
T.Ratio.3	1,120440	1,127990	1,064584
T.Rank.3	2,000000	1,000000	3,000000
S.Ratio.3	1,092394	0,979178	1,080367
S.Rank.3	1,000000	3,000000	2,000000
X.Ratio.3	1,075093	0,989138	1,003429
X.Rank.3	1,000000	3,000000	2,000000
T.Ratio.4	1,084824		
T.Rank.4	1,000000		
S.Ratio.4	1,127061		
S.Rank.4	1,000000		
X.Ratio.4	1,117767		
X.Rank.4	1,000000		
T.Ratio.5	1,092300		1,043531
T.Rank.5	1,000000		2,000000
S.Ratio.5	1,120519		1,084893
S.Rank.5	1,000000		2,000000
X.Ratio.5	1,113627		1,004778
X.Rank.5	1,000000		2,000000

Source: Author

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 sets. In total, we are working with 36 variable sets (two networks do not use all three input variables). The depreciation of fixed assets is not the most important value in any of the preserved neural structures. Personnel costs are defined in only three cases as the most important value - i.e. ranked in the first place. In other cases, therefore the vast majority of the sets, the most important value is materials and energy consumption. Thus it is obvious that material consumption is a relatively major production input.

Conclusion

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

The aim of the paper has been met. The best neuron structures were generated and retained. The most appropriate among them seems to be GRNN 1:1-11-2-1:1, despite only considering a single factor of production - materials and energy consumption. It is thus obvious that production in the Friall company is materially demanding and so there is no need to take the remaining two variables into account for the prediction. This has emerged from the sensitivity analysis.

The proposed neural structure is applicable in practice when compiling the 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 demand for the company's products is not limited. It further assumes that only productive capacities can be limited in this case.

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