Cash Management of a Company Using Neural Networks

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Abstract

Cash management is one of the most important indicators of a company´s activities and plays an important part in decision-making. Cash management or cash flow management are incomes and expenses for a certain period. The aim of cash management is to mobilize, check and plan a company´s financial resources, which is not easy. The aim of financial managers is to find an effective and flexible tool for improving the processes for the optimization of cash management. One such tool appears to be a system of artificial neural networks. These networks are very flexible and outperform other models, including linear regression models, in many ways. However, networks also have certain pitfalls, which include the sensitivity of the input data, the longer time associated with training the networks, as well as the lack of possibilities to define the architecture and other parameters of the network. This article attempts to predict the future development of various kinds of cash flows. In so doing, it hopes to identify a suitable neural network that is able to predict these cash flows. This process involved the generation of 1000 accidental artificial neural structures, of which the 5 most suitable were preserved. A sensitivity analysis was subsequently carried out. The results of the research show that neural networks can be effectively used to predict the cash flow developments within a company.

Keywords: cash management, cash-flow, artificial neural network, model

Introduction

Cash management plays an important role in company decision-making. Kroes and Manikas (2014) state that a company´s cash policy is inexorably linked to the company´s operations and includes, for example, working capital in the form of cash receivables from customers, inventory holdings, and cash payments to suppliers. Cash management within companies was one of the first areas to which mathematical programming and operations research was applied.

Cash management is the same as cash flow management. Cash flow management presents the cash inflows and outflows achieved over a certain period of time and is a component of the annual financial statements (Danciu 2013). The functions of cash management include the mobilization, control and planning of the financial resources of a company (Tichý 2008). All companies should minimize the costs associated with the maintenance or lack of cash (Lehutová, Križanová and Kliештik 2013).

According to Pacheco and Morabito (2011), the management of cash flow in a company is a complex financial problem that involves balancing the short-term investments, cash receipts and expenditures, and short-term debts of the company, in order to maximize the financial cash return at the end of a planning horizon. This also encompasses the supply of financial resources for the operating activities of a company. The cash flow management problem includes the formulation of decision rules to control the level of cash balances and the administration of a set of facts structured in time (Brigham and Houston 2013).

According to Kroes and Manikas (2014) a company´s cash flow can be manipulated in three ways, through changes to the:

- time from when goods are sold until the revenue is collected by the company;
- company´s inventory levels;
- time that the company takes to pay its vendors.

Pacheco and Morabito (2011) analysed the viability of applying network models and evaluated their performance in companies in practice. He, Bai and Dong (2011) created a management and control model for cash flow within a company – the model is composed of two parts: strategic management of cash flow and tactical management of cash flow. Other authors, for example, Dong and Li (2014), explored the issue of cash flow risk management strategies.

The management of cash balances is a constant problem in all companies. Moraes and Nagano (2014) claim that this is due to the daily inflows and outflows of cash, irrespective of whether these are generated through the activities of the company or through financial transactions that it negotiated. There is a need to control financial resources in order to obtain the best results for the company (Šalaga and Berzáková 2014). Nevertheless, it is not easy to define the amount of money to be maintained in cash. The objective of many financial managers is therefore to find a flexible and effective tool which improves the process of optimizing cash management. In recent years, the use of artificial neural networks (ANNs) has become popular for this purpose. ANNs can provide comprehensive insights into something that is difficult to obtain through the application of other methodologies.

ANNs are universal and highly flexible function approximators, which were first used in the fields of cognitive science and engineering (Simutis et al. 2007). ANNs focus primarily on computing and storing information within a structure composed of many neurons. According to Cheng, Tsai and Liu (2009), these networks imitate the human brain in terms of learning, recall and generalization, and are usually designed to solve non-linear or ill-structured problems. In recent years, the application of ANNs has become increasingly popular in company management. They are used for tasks such as pattern recognition, classification and time series forecasting (Vochozka and Rowland 2015). One of the most important components in the success of neural networks is the structure of the ANNs and the data necessary to train the network (Michal et al. 2015). ANNs typically introduce a nonlinear equation into a specified layer. This allows networks to easily capture high order correlations and effectuate nonlinear mapping (Cheng, Tsai and Sudjono 2012). ANNs are more appropriate than linear regression models and other models because ANNs capture decision-making complexities more clearly, predict more accurately, are more robust with regards to missing data, and their performance is not affected by multicollinearity (Namazi, Shokrolahi and Maharluie 2016).

One of the problems that ANNs can face is that of overtraining or over sensitivity to the input data. Dvořáková and Vochozka (2015) touch on another problem; the lack of clear rules for defining the architecture and the different parameters of a network (the most common way to determine the optimal architecture is simply by trial and error). In addition, the training of the network is usually a lot more time-consuming than by other methods (Vochozka and Sheng 2016).

As such, ANNs are not yet widely applied to cash management in companies. In the majority of cases, the application of ANNs has been experimental, and in particular linked to the banking sector and to ATM cash management (Dilijonas and Zavrid 2008; Dilijonas et al. 2009; Venkatesh et al. 2014; Ágoston, Benedek and Gilányi 2016; and more). Furthermore, ANNs in practice are usually used for predicting future business developments, inventory management, cost modelling, assessing the creditworthiness of customers, determining financial plans, providing bank loans or for determining the value of a company.

The main aim of doing business is to generate profits. However, in recent years, many experts have begun to refer to the drawbacks of using profit as a top indicator. They argue that there is a time inconsistency between the income and revenues, and costs and expenses, which generate the receivables and liabilities for a company. This means that the profit may not be purely based on money. This is reflected in the fact, that there have been many cases where companies have fallen into secondary insolvency, i.e. they generate profit, but cannot pay their liabilities. For this reason, the growth in shareholder value is now more often being flouted as the main aim of a company (Kislingerová 2010). This attitude is firmly connected with Value Based Management. One of its pillars is focused on cash flow. To summarize, to create shareholder value, it is necessary to generate cash stocks and ideally free cash flows, i.e. cash flows which may be withdrawn from the company without having a negative impact on its operations.

Cash flow is therefore one of the most important indicators of company activity and the planning thereof is an integral part of a financial manager´s job.

The aim of this study is to apply neural networks to cash flow planning in a specific company.

Materials and Methods

Our model company is Hornbach, a DIY (Do-It-Yourself) store that sells products for home and garden improvements.

For the purposes of the study an analysis was conducted of the time lines of the individual cash flows within the company with a view to predicting their future development. The following cash flows were identified:

1. Net cash flow from operating activity before tax, changes in operating capital and extraordinary items (further A*),
2. Net cash flow from operating activity before financial items, tax and extraordinary items (further A**),
3. Net cash flow from operating activity (further A***),
4. Net cash flow relating to investment activity (further B***),
5. Net cash flow relating to financial activity (further C***),
6. Net increase, or decrease in financial means (further F),
7. The state of financial means and cash equivalents at the end of the accounting period (further R).

The data for each of the identified cash flows were available for the years 1998-2016 (i.e. as on the day the statements were draw up – in reality 1997-2015). The used data set was considered to be sufficient to fulfil the aim of this study. However, it would also have been possible to use the bi-annual or quarterly data, but training the neural network would have been lengthier.

MS Excel was used for the preparation of the data file. DELL Statistica software (versions 7 and 12) was used for the calculations. The results of these calculations were subsequently processed by the automatized neural networks.

The purpose of the above was to identify an artificial neural network (three-layer or four-layer perceptron neural network), which would be able to predict the future development of the identified Hornbach cash flows.

All the used values were continuous. The data was split into three groups:

- Training: 70 %
- Testing: 15 %
- Validation: 15 %

The seed for the random choice was fixed at a value of 1000. Subsampling took place randomly.

In total, 1,000 random artificial neural structures were generated, of which the 5 most suitable were retained. The most appropriate neural structures were selected based on the lowest error rate, and vice versa on the highest predictive power (see Table 1)[1].

The following types of neural networks were applied:

1. Linear neural networks (hereinafter referred to as Linear)
2. Generalized regression neural networks (hereinafter referred to as GRNN)
3. Neural networks – radial basic function (hereinafter referred to as RBF)
4. Multiple perceptron neural networks – three layers (hereinafter referred to as MLP)
5. Multiple perceptron neural networks – four layers (hereinafter referred to as MLP).

The following activation function was used for the hidden and output layer of neurons:

1. *Linear function:*

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

where:

y	is output;
k	is transmitting function;
x	is input;
w	is synaptic weight.

2. *Sigmoid function:*

$$S(t) = \frac{1}{1 + e^{-t}} \tag{2}$$

A maximum of 5 neurons were used in the hidden RBF layers.

A maximum of 11 neurons were used in the hidden three-layer perceptron networks.

A maximum of 11 neurons were used in the hidden layers of the four–layer perceptron networks.

All the other settings were default settings.

A sensitivity analysis was subsequently conducted to determine the most appropriate and the most accurate neural structures. In this way, we determined how the development of the individual cash flows is dependent on time.

Results and Discussion

The application of the methodology outlined in this article produced the five most suitable neural networks presented in Table 1.

[1] Determined by the method of smallest squares. If the differences between the newly generated networks are no longer essential, the training comes to an end.

Table 1: Generated and preserved neural structures

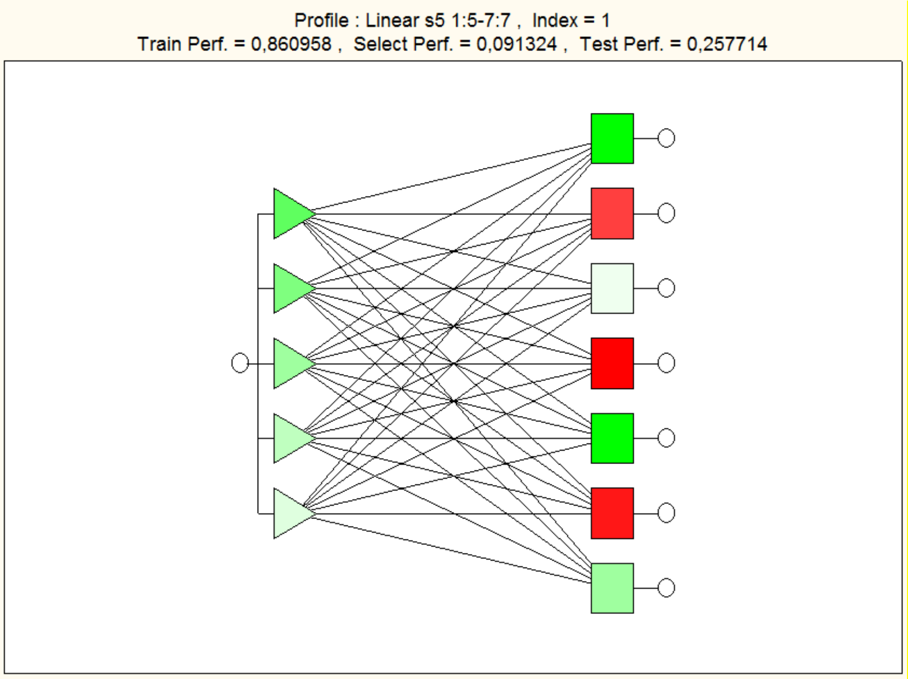
	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Training/ Members	Inputs	Hidden (1)	Hidden (2)
1	Linear s5 1:5-7:7	0.860958	0.091324	0.257714	1.499147	1.537050	1.510939	PI	1	0	0
2	MLP s5 1:5-11-11-7:7	0.244904	0.323720	0.014999	0.357907	0.123054	0.340600	BP1b	1	11	11
3	RBF s5 1:5-2-7:7	0.362111	0.467259	0.210522	0.000014	0.000025	0.000025	KM,KN,PI	1	2	0
4	RBF s5 1:5-3-7:7	0.107195	0.182759	0.669986	0.000006	0.000017	0.000028	KM,KN,PI	1	3	0
5	GRNN s10 1:10-5-8-7:7	0.120684	0.801228	0.421092	0.000006	0.000016	0.000029	SS	1	5	8

Source: Author

The list of preserved networks is quite manifold and includes a linear neural network, a four-layer perceptron network, two basic radial function neural networks, and a generalized regression neural network. Based on the assignment, all of them only use one input value, i.e. time.

The scheme for network one, i.e. Linear s5 1:5-7:7, is presented in Figure 1. As can be seen, the network uses five neurons in the first layer and seven neurons in the output layer, as determined by the number of output values.

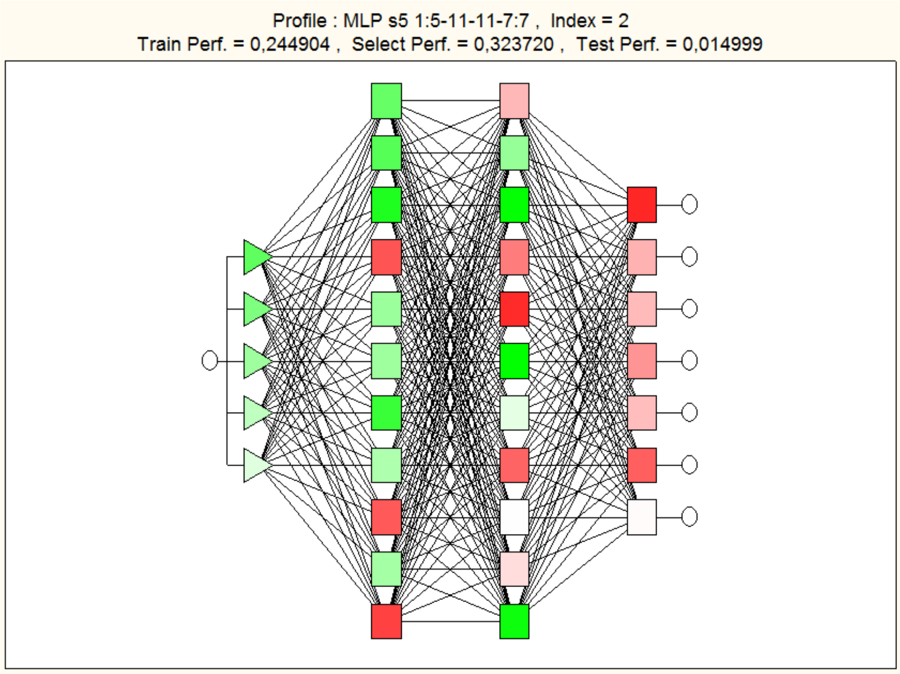
Figure 1: Scheme for Linear s5 1:5-7:7



Source: Author

The scheme for the second retained network is presented in Figure 2.

Figure 2: Scheme for MLP s5 1:5-11-11-7:7

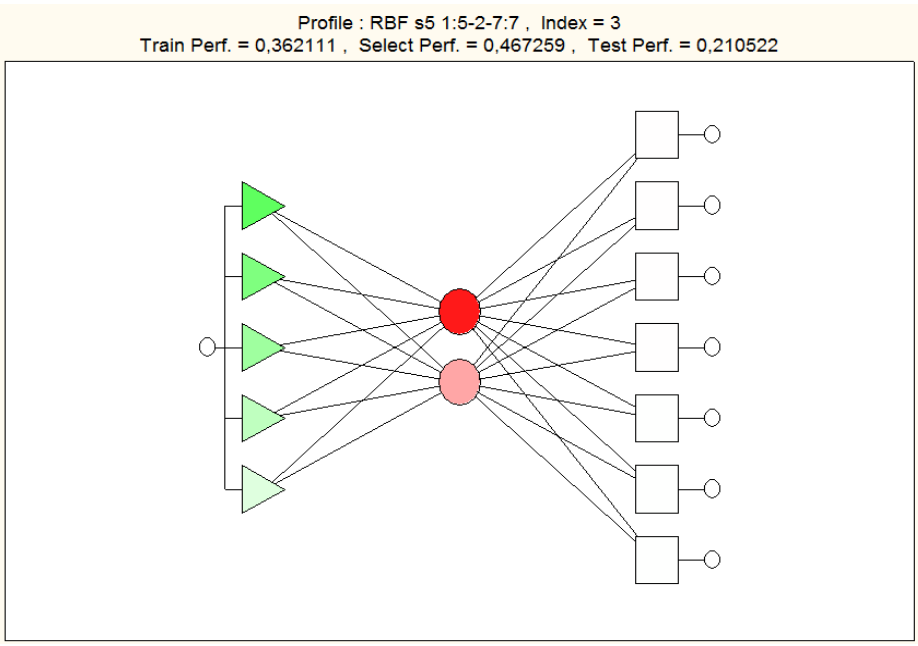


Source: Author

The four-layer-perceptron neural network MLP s5 1:5-11-11-7:7 also uses one input and generates seven outputs, thereby utilising eleven neurons in both hidden layers.

The scheme for the retained RBF neural network is presented in Figure 3.

Figure 3: Scheme for RBF s5 1:5-2-7:7

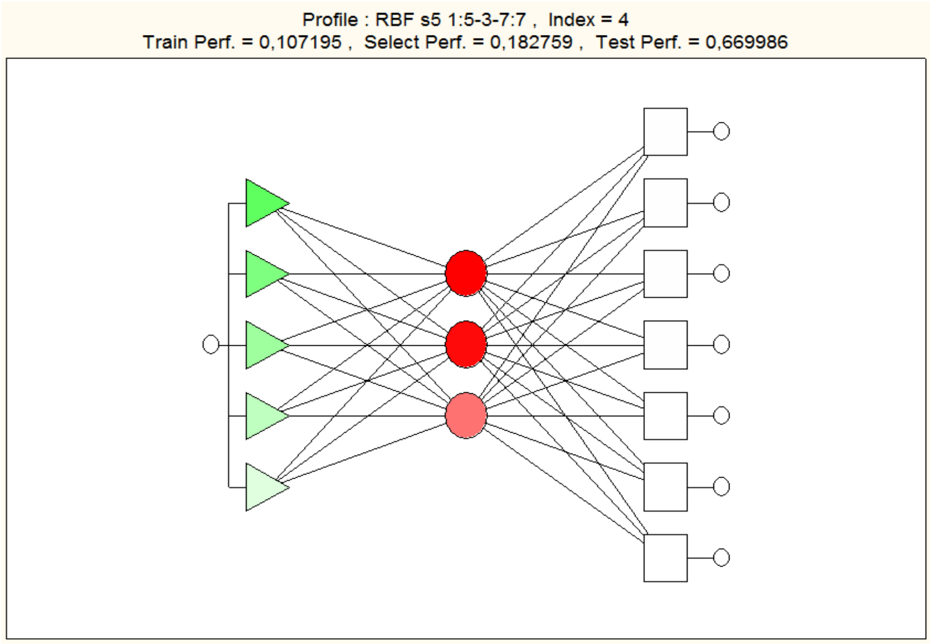


Source: Author

In this case, the neural network uses two neurons in its hidden layer.

The scheme for the fourth retained neural network, once again of the RBF type, is presented in Figure 4.

Figure 4: Scheme for RBF s5 1:5-3-7:7

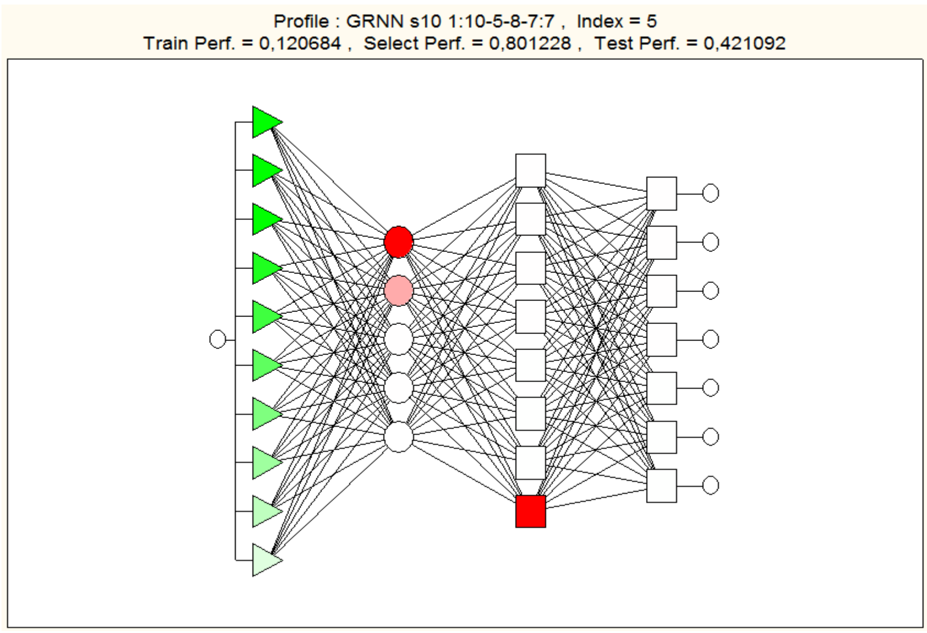


Source: Author

In this case, RBF s5 1:5-3-7:7 uses three neurons in its hidden layer.

The scheme for the fifth retained neural network is presented in Figure 5.

Figure 5: Scheme for GRNN s10 1:10-5-8-7:7



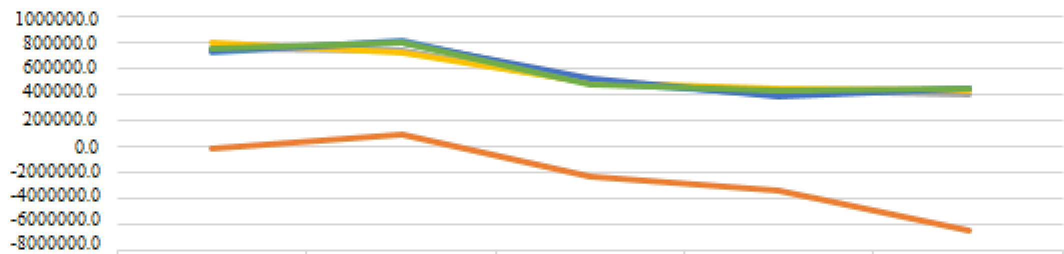
Source: Author

The last of the generated neural networks is the generalized regression neural network GRNN s10 1:10-5-8-7:7. The structure utilizes five neurons in the first hidden layer and eight neurons in the second hidden layer.

It was difficult to determine which of the generated and retained networks was able to best predict the future development of cash flows for the enterprise. It was therefore considered suitable to eliminate those networks for which the residua were higher on average, i.e. where they differ more from the reality in the evaluated period. For this reason, we evaluated each cash flow separately through a prism of all the generated and retained neural networks.

Figure 6 presents the real course of the net cash flows from operating activities before tax, changes in operating capital and extraordinary items for the followed period, as well as the course of the functions used to predict this cash flow in the identical period.

Figure 6: Predicted and actual net cash flows from operating activities before tax, changes in operating capital and extraordinary items



	2008	2009	2012	2013	2016
A*	731981.0	824239.0	495243.0	4044785.0	447078.0
A*.1	-14669	90195	-224396	-329260	-643850
A*.2	760555.1	746266.2	500088.1	428672.9	408157.7
A*.3	807598.3	723523.2	497845.3	447760.3	426598.9
A*.4	742092.7	806577.7	522285.1	383774.2	448596.3
A*.5	754641.6	801568.9	473035.4	427004.1	447076.3

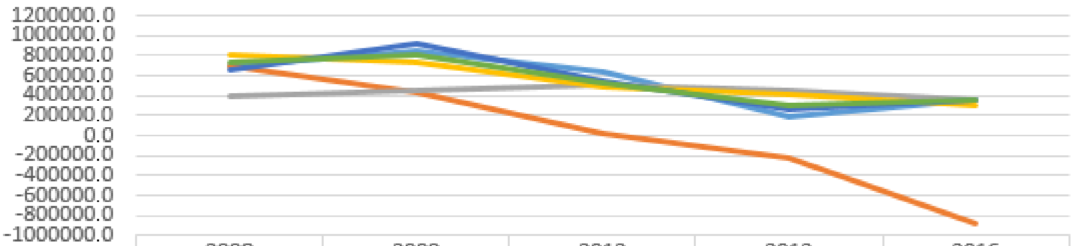
A* A*.1 A*.2 A*.3 A*.4 A*.5

Note: Values are stated in TCZK (thousands of Czech Crowns)
Source: Author

A* represents the real course of the cash flow. The other curves are identified according to the relevant number allocated to the retained neural network (see Table 1). It is evident from Figure 6 that neural network 1 falls outside the acceptable values. In contrast, the other networks optically predict the course of the cash flow.

The predicted and actual net cash flows from operating activities before financial items, tax and extraordinary items are presented in Figure 7.

Figure 7: Predicted and actual net cash flows from operating activities before financial items, tax and extraordinary items



	2008	2009	2012	2013	2016
A**	688638.0	853818.0	646938.0	191252.0	356192.0
A**.1	688177	439714	25611	-222852	-885418
A**.2	389546.3	450987.5	505428.0	458376.4	354095.3
A**.3	800977.4	731228.7	490157.4	416595.0	297879.5
A**.4	651092.7	919395.2	546529.5	269266.1	350554.6
A**.5	729209.9	813240.9	535021.2	303180.3	356185.2

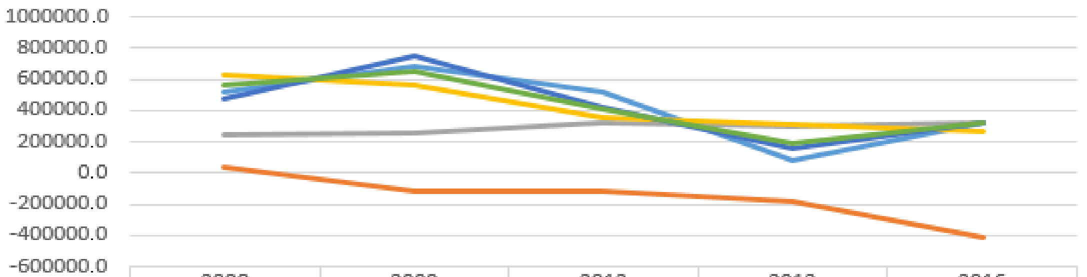
Note: Values are stated in TCZK

Source: Author

A** represents the real course of the cash flow. The other curves are identified according to the relevant number allocated to the retained neural network (see Table 1). It is evident from Figure 7 that neural networks 1 and 2 are not reliable predictors and are therefore not usable.

The predicted and actual net cash flows from operating activities are presented in Figure 8.

Figure 8: Predicted and actual net cash flows from operating activities



	2008	2009	2012	2013	2016
A***	516798.0	687541.0	518595.0	78138.0	326206.0
A***.1	40050	-112300	-112300	-188476	-417002
A***.2	242037.8	255502.9	316825.8	299958.6	322024.6
A***.3	632205.2	561438.7	358514.7	308647.8	266471.5
A***.4	478874.1	753779.4	417174.1	156938.6	320511.7
A***.5	558736.3	645598.8	410417.5	186328.4	326195.8

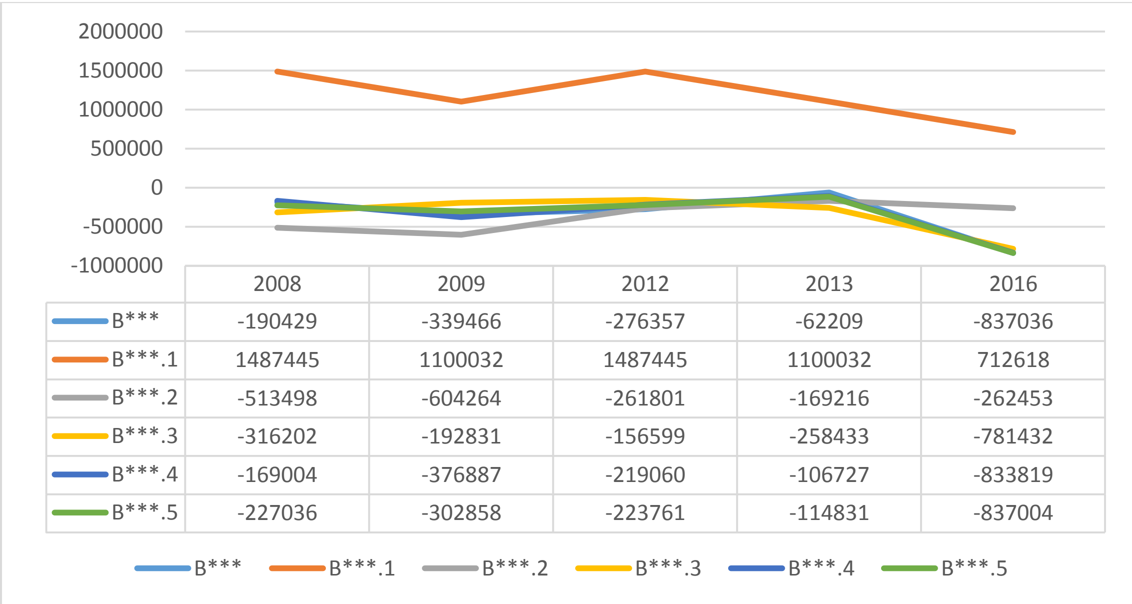
Note: Values are stated in TCZK

Source: Author

A*** represents the real course of the cash flow. The other curves are identified according to the relevant number allocated to the retained neural network (see Table 1). It is evident from Figure 8 that neural networks 1, 2 and 3 are not usable, although network 3 shows a smaller deviation than networks 1 and 2.

The predicted and actual net cash flows relating to investment activities are presented in Figure 9.

Figure 9: Predicted and actual net cash flows relating to investment activities



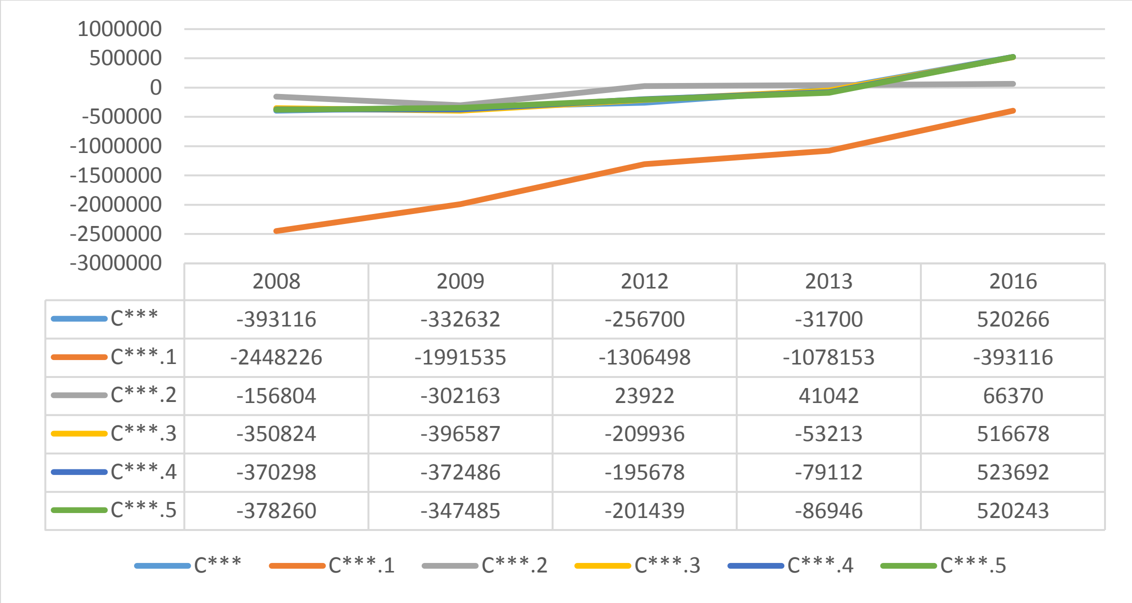
	2008	2009	2012	2013	2016
B***	-190429	-339466	-276357	-62209	-837036
B***.1	1487445	1100032	1487445	1100032	712618
B***.2	-513498	-604264	-261801	-169216	-262453
B***.3	-316202	-192831	-156599	-258433	-781432
B***.4	-169004	-376887	-219060	-106727	-833819
B***.5	-227036	-302858	-223761	-114831	-837004

Note: Values are stated in TCZK
Source: Author

B*** represents the real course of the cash flow. The other curves are identified according to the relevant number allocated to the retained neural network (see Table 1). It is evident from Figure 9 that the neural structures of networks 1, 2 and 3 are not reliable and therefore cannot be used, although the deviation for networks 2 and 3 is smaller.

The predicted and actual net cash flows for financial activities are presented in Figure 10.

Figure 10: Predicted and actual net cash flows for financial activities



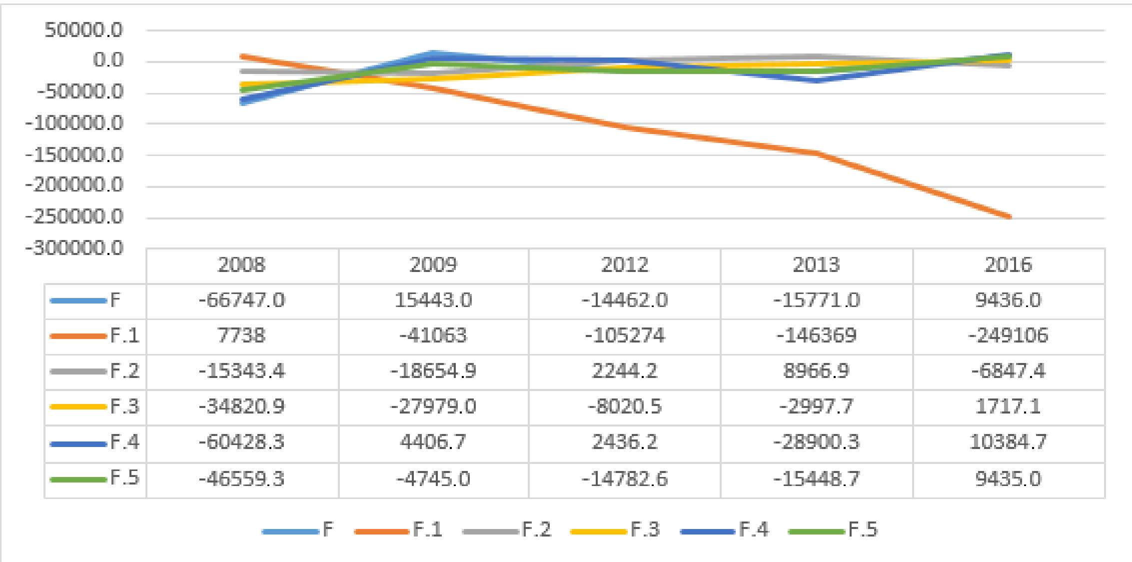
	2008	2009	2012	2013	2016
C***	-393116	-332632	-256700	-31700	520266
C***.1	-2448226	-1991535	-1306498	-1078153	-393116
C***.2	-156804	-302163	23922	41042	66370
C***.3	-350824	-396587	-209936	-53213	516678
C***.4	-370298	-372486	-195678	-79112	523692
C***.5	-378260	-347485	-201439	-86946	520243

Note: Values are stated in TCZK
Source: Author

C*** represents the real course of the cash flow. The other curves are identified according to the relevant number allocated to the retained neural network (see Table 1). It is evident from Figure 10 that neural network 1 and possibly 2 are unusable.

Figure 11 shows the predicted and actual net increase or decrease in financial means, i.e. cash.

Figure 11: Predicted and actual net increase or decrease in cash



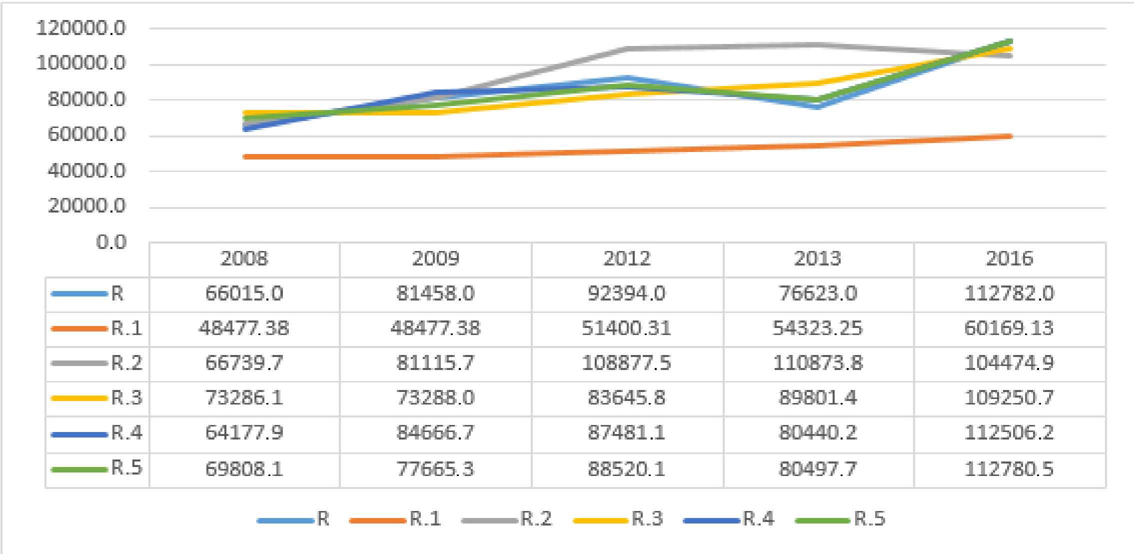
	2008	2009	2012	2013	2016
F	-66747.0	15443.0	-14462.0	-15771.0	9436.0
F.1	7738	-41063	-105274	-146369	-249106
F.2	-15343.4	-18654.9	2244.2	8966.9	-6847.4
F.3	-34820.9	-27979.0	-8020.5	-2997.7	1717.1
F.4	-60428.3	4406.7	2436.2	-28900.3	10384.7
F.5	-46559.3	-4745.0	-14782.6	-15448.7	9435.0

Note: Values are stated in TCZK
Source: Author

F represents the real course of the cash flow. The other curves are identified according to the relevant number allocated to the retained neural network (see Table 1). It is evident from Figure 11 that the most suitable neural network is network 5, i.e. GRNN s10 1:10-5-8-7:7.

The predicted and actual state of cash and cash equivalents at the end of accounting period are presented in Figure 12.

Figure 12: Predicted and actual state of cash and cash equivalents at the end of accounting period.



Note: Values are stated in TCZK

Source: Author

R represents the real course of the cash flow. The other curves are identified according to the relevant number allocated to the retained neural network (see Table 1). It is evident from Figure 12 that the best neural network is network 5, and if there is tolerance for a small deviation also network 4.

Table 2 provides a summary of the usability of the individually retained neural structures.

Table 2: Evaluation of the retained neural networks

Neural network	A*	A**	A***	B***	C***	F	R
Linear s5 1:5-7:7	NO	NO	NO	NO	NO	NO	NO
MLP s5 1:5-11-11-7:7	YES	NO	NO	NO	NO	NO	NO
RBF s5 1:5-2-7:7	YES	YES	YES	NO	YES	NO	NO
RBF s5 1:5-3-7:7	YES	YES	YES	YES	YES	NO	YES
GRNN s10 1:10-5-8-7:7	YES	YES	YES	YES	YES	YES	YES

Source: Author

On the basis of the results of the performed analysis, we can conclude that the most reliable and useful neural structure is that of network 5, i.e. GRNN s10 1:10-5-8-7:7, followed very closely behind (and still usable) by neural network 4, i.e. RF s5 1:5-3-7:7.

Conclusion

The aim of this study was to apply neural networks to cash flow planning in a specific company, namely Hornbach.

As part of the study, neural structures were generated, of which the five best were retained. The principle differences were identified between the predicted and actual values for the individual networks, which were then subjected to a sensitivity analysis. The results of this analysis showed that the most reliable and suitable network was a generalized regression neural network (i.e. GRNN s10 1:10-5-8-7:7). This network was found to be able to accurately predict various kinds of cash flows within Hornbach. Similarly, but with a more limited application, the radial basic function neural network RBF s5 1:5-3-7:7 was found to be accurate, but not highly accurate, in predicting the state of cash and cash equivalents at the end of the accounting period. The other networks were shown to be largely inaccurate and therefore not usable in practice.

On the basis of the results of the study, it can be concluded that neural networks can be successfully and effectively applied by companies for predicting developments in cash flows. However, it should be noted that each company must generate its own unique neural structure(s) to do so.

The suggested neural structures can be used in practice for drawing up the financial plans of a company (as was verified in the case of Hornbach). To modify the result, it is possible to use the causal or intuitive methods of financial planning.

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ŠULEŘ, P., 2016. Cash Management of a Company Using Neural Networks**.** *Littera Scripta* [online]. České Budějovice: The Institute of Technology and Business in České Budějovice, **9**(3), 125-140[accessed: 2016-12-20]. ISSN 1805-9112. Available at: http://journals.vstecb.cz/category/littera-scripta/9-rocnik/3_2016/.