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THE APPLICATION OF ARTIFICIAL NEURAL NETWORKS ON THE PREDICTION OF THE FUTURE FINANCIAL DEVELOPMENT OF TRANSPORT COMPANIES

It is logical that in an uncertain economic environment it is necessary for companies to be able to plan better, to report more precisely and to be able to better evaluate their future financial development. For their analysis, the authors of this article focus on a particular segment of the national economy, namely transport and freight forwarding companies.

The aim of this article is to utilize artificial neural networks to predict potential financial problems in transport companies in the Czech Republic.

Data on all companies involved in transport and freight forwarding in the Czech Republic for the period 2003 - 2013 were used for modelling the particular neural network. The data file contained nearly 15,000 records on companies for the individual years. These records included both financial statement data and non-accounting data (e.g. data on company employees).

The following networks were used for modelling the neural network: a linear network, a probabilistic neural network (PNN), a generalised regression neural network (GRNN), a radial basis function network (RBF), a three-layer perceptron network (TLP) and a four-layer perceptron network (FLP).

The analysis resulted in a concrete model of an artificial neural network. The neural network is able to determine with more than ninety per cent accuracy whether a company is able to overcome potential financial problems, within how many years a company might go bankrupt, or whether a company might go bankrupt within one calendar year. The text also includes the basic statistical characteristics of the examined sample and the achieved results (sensitivity analysis, confusion matrix, etc.).

The model can be utilized in practice by transport company managers, investors looking for a suitable company for capital investment, competitors, etc.

Keywords: Transport company, financial problems, prediction, neural network, model.

1. Introduction

Youssef Mohamed, Kumar and Motwani [1] evaluated selected variables of 165 production companies and transport companies in America. They analysed the ability of the companies to respond to the needs of their internal and external environments. They found out that significant differences exist between a transport company and a production company. Youssef Mohamed, Kumar and Motwani [1] claim that a transport company can be exactly identified and classified according to its response to the external environment.

Nowadays, companies use quality, the environment, health protection and safety management as tools with which to resolve certain problems. This also applies to transport companies [2].

Pavolova, and Tobisova [3] describe and assess in detail the quality management of suppliers to a particular transport company in Slovakia and put forward potential models for evaluating them, particularly in relation to the overall performance of the company.

Bielikova and Misankova [4] explain the importance of company culture, its establishment, development and application through research work carried out in a transport company. The authors claim that company culture is influenced by the permanent confrontation with business priorities and with the external dynamics of the environment in which it operates. The authors conclude by putting forward a new model for company culture in the analysed company

Litvaj, Ponisciakova, Stancekova and Drbul [5] focused on the processes in small transport companies, in one company in

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particular, thereby characterizing the importance of knowledge management. The authors acknowledge that knowledge management is the basis of successful company management. The management of transport companies depends on numerous aspects that have to be taken into account. Each of these aspects directly and/or indirectly influences the viability of a company. The viability increases with good management of the individual company areas and by unifying planning activities, budgets, accounting, etc. [6]. Effective management systems are essential if a company is to improve and develop its products and services in order to be and stay successful in the market. It is in the interest of a company's market position to monitor the development of standards and resulting changes [2].

Kubecova and Petrach [7] evaluated the performance of 775 small transport companies in the Czech Republic for the period 2008 - 2012. They found that the number of legal entities active in long haul freight transport (international) grew during the period, whereas the number of companies involved in short haul freight transport (domestic) decreased.

Kovbatiuk and Shklyar [8] evaluated anti-crisis measures implemented by a transport company by means of production indicators and their financial situation (profitability index, business activity index, financial index, and manufacturing opportunity index). Verschoor and L. Reijnders [9] evaluated the viability of transport companies. They came to the conclusion that none of the monitored companies used the life cycle method appropriately. In four cases the life cycle studies were assessed from outside the company. The results of applying the life cycle method were used to reduce external risks, for databases or for the purchasing departments in five of the companies. Only two of the monitored companies assessed the risks correctly.

Zelin and Xunyin [10] defined the main factors that influence competitiveness and used them as indicators for evaluating company strategies and subsequently the strategic stages of a company's life. Unfortunately, all companies insufficiently defend themselves against the dangers that attack the environment in which they operate which decreases their viability [9]. But in fact the theory of company life cycle has been used for a long time [10].

Ponisciakova, Sukalova [6] characterize the important aspects of management in transport companies e.g. management of services, assets, value, human resources, and qualifications. They also deal in detail with management as a tool, which is utilized in various company spheres to unify activities within a company that are often dealt with separately. Zelin and Xunyin [10] present the key factors affecting competitiveness and use these to evaluate various company strategies and the individual stages of a company's life. They also put forward options for the strategic transformation and reform of companies.

De Vries, Lukosch and Pijper [11] accept the need for quick changes in regulations and the organization of the transport sector and consider the need for innovation within transport companies

as inevitable. They also propose that competent persons in company management should define a strategy they will jointly adhere to. Sukalova, Ponisciakova [12] suggest that increased innovation in all aspects of life is a characteristic of this period of time. Innovation is an absolute necessity for a transport company. The ability to cope with changes in legislature, economic circumstances and other areas depends on an organization's ability to learn. A sustainable strategy is important for improving a company's viability. An integrated portal built on information, communication, learning and performance improvement is the solution. In situations where such a portal already exists, the utilization thereof is usually insufficient and needs to increase [11].

The management of any company, within the transport sector or elsewhere, depends on the environment in which it operates. The present time is characterized by the increasing dynamics of innovation in all spheres of social and economic life. Information and telecommunication technologies are developing rapidly and the importance of knowledge is growing [12].

Cai, Cai and Yang [13] present the traditional theory of viability as a combination of internal and external factors such as an open and fully competitive market, weak government intervention policy, independent innovation, entrepreneurial spirit, etc. Nowadays, the entrepreneurial environment is characterized by globalisation and internationalisation. In conditions where there are constant changes in the entrepreneurial environment, the methods and tools for crisis management and risk management have to be integrated into change management [12].

The ability to predict the future is a necessity for all companies operating in a market [14]. Chu and Widjaja [14] see predicting as the basis for decision making in most organizations. Accurate predictions about the future will determine a company's success. However, such decisions are not easy. Numerous methods are available to decision makers and selecting the right one requires extensive knowledge of statistics and good personal judgement.

Neural networks have successfully been applied to the identification (or classification) of healthy economic entities and those inclined to bankruptcy, as well as for the prediction of inflation and deflation, exchange rates and the prices of shares [15]. In contrast, Adya and Collopy [16] came with the opinion that the application of neural networks still gives rise to mixed results. They evaluated several studies and found that eleven of them were effectively verified and implemented with positive results, whereas others were effectively verified but encountered problems in their implementation. Nearly all the studies supported the potential of artificial neural networks to predict.

Artificial neural networks provide powerful models for the solution of numerous economic classifications as well as regression problems. This is why neural models are now included in most standard statistical software packages [15]. Weinlichova and Stencl [17] came with the possibility of applying artificial intelligence by means of neural networks. They found an

opportunity to apply neural networks to managerial information systems. Neural networks have also successfully been utilized to predict exchange rates, however with the large quantity of parameters that need to be estimated, it is not easy to choose the appropriate networks. Scientists often overlook the influence of neural network parameters on the prognostic performance of a neural network. They also find that neural networks are often better than linear models, but only for short-term prognoses [18]. Weinlichova and Stencl [17] admit there are other possibilities for data processing apart from the tried and tested methods i.e. managerial information systems and business intelligence – namely by means of neural networks. Weinlichova and Stencl [17] monitor and describe this possibility in detail and compare it with existing possibilities.

The current interest in artificial neural networks for prediction purposes has led to a huge growth in research activities during the last ten years. Zhang, Patuwo and Hu [18] suggest that scientists are not completely sure about the influence of key factors for predictions on the performance of artificial neural works. Weinlichova and Stencl [17] present several possible applications of neural networks to various types of tasks in a managerial information system.

This contribution aims to utilize artificial intelligence, namely artificial neural networks, for the prediction of the future development of transport companies. Atrial will be performed with a concrete group of transport and freight forwarding companies.

The research hypothesis is set as follows: “Artificial neural networks can be utilized to predict the future development of transport companies”.

2. Materials and analytical methods

The basic information on companies that is to be used for the analysis comes from the Albertina database. The data covers those companies classified by the Czech Statistical Office as transport companies. These companies fall into groups 49 (land and tube transport), 50 (water transport) and 51 (air transport) of the CZ-NACE classification (classification of economic activities). The final sample includes data on all companies that have transport as their core business in the Czech Republic and were operating on the market in the period 2003 - 2013. The data is processed into tables. Each line contains company development parameters for one company by year. The final sample contained exactly 14,874 data lines. Each line consisting of one hundred characteristics. These characteristics are financial and non-financial indicators.

The financial parameters include all the data from a company's financial statements: balance sheet; profit and loss statement; and cash flow statement. The earnings before interest and taxation (EBIT) is also used.

The non-financial indicators include: company identification (name and registration number); region of activity; number of employees; and the auditor's statement.

On the basis of the input data we sought an artificial neural structure that would be able to classify each company into one of the following three groups: solvent company, will go bankrupt in the current year and will go bankrupt in the future.

First we determined the characteristics of the individual companies. We then defined the quantity of the output category. These were defined on the basis of the values presented in the column “final status” in the Excel sheet. For this purpose it is essential to know the results for each year of the period 2003 - 2013. It is on this basis that the category input values were set. These are non-financial indicators. All the items shown from the financial statements are continuous quantities.

After this process the sample was randomly divided into three groups of companies: a training group (the neural networks are trained on this group to achieve the best possible results); verification group (the success of the classification of the trained neural structures is tested on this group); and the validation group (used for second verification of the obtained results). The data was divided into the training, verification and validation groups in the following proportions: 70:15:15.

Costea [19] created several maps in which each company was located to a certain period and subsequently selected the best one which could be used for the analysis of a company over the course of time.

We can therefore claim that artificial neural networks can also be used for the classification of solvent, bankrupt and potentially bankrupt companies in cases where the input data are not limited to financial indicators because non-financial indicators can also be used.

Once this exercise was completed, 10,000 artificial neural structures¹ were generated, of which the 10 most suitable were retained. For the model, linear neural networks (Linear), probabilistic neural networks (PNN), generalised neural networks (GRNN), radial basis function neural networks (RBF), three-layer perceptron networks (TLP) and four-layer perceptron networks (FLP), were utilised.

For the radial basis function neural network we used 1 - 3,696 hidden neurons. The 2nd layer of the three-layer perceptron network contained 1 - 100 hidden neurons. The 2nd and the 3rd layers of the four-layer perceptron network both also contained 1 - 100 hidden neurons. The perceptron networks classified the individual companies on the basis of entropy. The classification threshold was assigned on the basis of the highest confidence.

¹ Unless the improvement in the individual trained networks is significant the training of neural networks can be shortened

3. Results

On the basis of the parameters 10,000 artificial neural networks were randomly generated. The 10 networks which showed the best results (i.e. the highest rate of correct classification of companies according to their credit worthiness and, as the case may be, the tendency to bankruptcy), were retained for further assessment and subsequent processing [Table 1].

The ninth retained artificial (the most suitable and usable one) neural network is a radial basic function. A schematic illustration of the neural network, RBF 55:68-337-3:1 [Fig. 1].

55 variables, discrete as well as continuous, enter the model. Table 2 shows the ten variables which have the greatest influence on the final classification according to the sensitivity analyses and the application of the model (as before, from the point of view of the validation group of companies).

All the weights fluctuate above 1. Although the weights are significant, they fluctuate just above 1. This is important with regards to the network's classification accuracy. It fluctuates at

the highest level of all the models assessed so far. The lowest value (that of the training group) fluctuates above 94.1%.

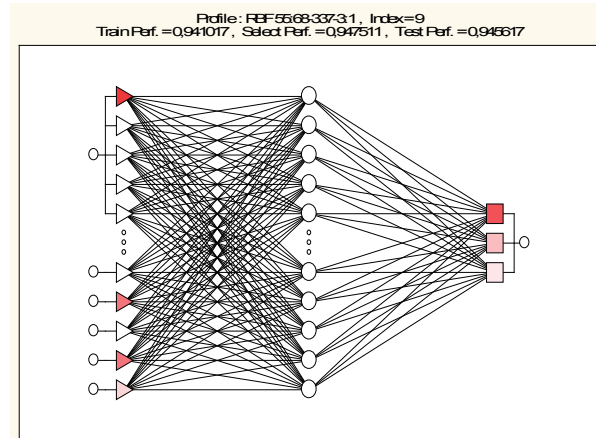


Fig. 1 Schematic illustration of artificial neural network RBF 55:68-337-3:1. Source: authors

Obtained neural networks showing the best potential to predict the future development of transport companies

Table 1

	Profile	Train Perf.	Select Perf.	Test Perf.	Train Error	Select Error	Test Error	Inputs	Hidden	
									(1)	(2)
1	MLP 1:14-38-3:1	0.939800	0.946429	0.945346	0.591421	0.559210	0.581395	1	38	0
2	MLP 1:14-51-3:1	0.939800	0.946429	0.945346	0.554447	0.532507	0.544601	1	51	0
3	MLP 1:14-34-58-3:1	0.939800	0.946429	0.945346	0.552794	0.529853	0.536205	1	34	58
4	Linear 2:2-3:1	0.939800	0.946429	0.945346	0.195252	0.184768	0.186567	2	0	0
5	Linear 1:1-3:1	0.939800	0.946429	0.945346	0.195251	0.184750	0.186551	1	0	0
6	PNN 38:54-7392-3:1	0.939800	0.946429	0.945346	0.194469	0.184331	0.186722	38	7392	0
7	PNN 39:55-7392-3:1	0.939800	0.946429	0.945346	0.194468	0.184331	0.186722	39	7392	0
8	RBF 32:45-337-3:1	0.940341	0.946699	0.945346	0.184744	0.181825	0.185517	32	337	0
9	RBF 55:68-337-3:1	0.941017	0.947511	0.945617	0.184981	0.181435	0.185941	55	337	0
10	RBF 76:92-337-3:1	0.941558	0.946970	0.945887	0.184503	0.181178	0.185548	76	337	0

Source: authors

Sensitivity analyses for network RBF 55:68-337-3:1 (10 selected most important variables)

Table 2

Input variable	T.Ratio. 9	T.Rank. 9	S.Ratio. 9	S.Rank. 9	X.Ratio. 9	X.Rank. 9
Long-term receivables - TCZK	1.05910	2.00000	1.05439	1.00000	1.04470	1.00000
Other operational costs - TCZK	1.05580	4.00000	1.04396	2.00000	1.04164	2.00000
Receivables & Debtors	1.05631	3.00000	1.03787	4.00000	1.03869	3.00000
Inventories - TCZK	1.04142	7.00000	1.04354	3.00000	1.03819	4.00000
Sales of goods - TCZK	1.05566	5.00000	1.03203	5.00000	1.02825	5.00000
Other short-term payables	1.03611	10.00000	1.02271	6.00000	1.02657	6.00000
Administration and other costs	1.02937	13.00000	1.01520	13.00000	1.01967	7.00000
Total trade payables (short term) - TCZK	1.04149	6.00000	1.02141	7.00000	1.01832	8.00000
Trade payables	1.04052	8.00000	1.02120	8.00000	1.01826	9.00000
Short-term payables - TCZK	1.03141	11.00000	1.01577	12.00000	1.01799	10.00000

Source: authors

Confusion matrix - extract of the generated neural network RBF 55:68-337-3:1

Table 3

Classification according to the individual neural networks	T. Solvent	T. Bankr. in future	T. Bankr. in current year	S. Solvent	S. Bankr. in future	S. Bankr. in current year	X. Solvent	X. Bankr. in future	X. Bankr. in current year
Solvent. 9	6943	337	94	3497	153	39	3493	156	44
Bankruptcy in future. 9	4	13	1	1	5	1	1	2	0
Bankr. in current year. 9	0	0	0	0	0	0	0	0	0

Source: authors

To obtain complete insight a confusion matrix was prepared. The matrix provides an extract of summary of the correctly and incorrectly classified companies in training, verification and validation [Table 3]. The companies of the training group are identified with T, of the verification group with S, and of the validation group with X.

4. Discussion

The confusion matrix confirms that all the artificial neural networks are able to predict relatively accurately which companies will survive. Their success rate is precise. For the majority of models this is approximately 100%. However, the aim of this article was not to find a model with which to predict companies that would not go bankrupt. The aim was to find a tool that could identify companies that could not survive possible financial problems, be it either in the current year or in the near future. The results of the confusion matrix disqualifies most of the retained neural networks. Only the radial basic neural networks i.e. networks 8, 9 and 10 qualify. The networks that predicted the highest number of bankrupt companies had the highest value in terms of accuracy. The difference between networks 9 and 10 was relatively small. However, network 9 (i.e. RBF 55:68-337-3:1) was more successful. This network also shows the highest accuracy with regards to the classification of the companies. For the training group the accuracy was equal to that of network 10. For the verification group network 9 was more successful. For the validation group the reverse was true, network 10 was more successful. The higher success rate of the classification may therefore be derived from the absolute value of the predicted future situation.

With a deeper analysis of network 9 (RBF 55:68-337-3:1) we can obtain interesting insights into the characteristics of each of the three groups of companies.

The summarisation of the results and the arguments put forward in the discussion confirm the hypothesis. Artificial neural networks are able to predict the future development of a company with a probability higher than 94%.

5. Conclusion

This contribution set out to apply artificial intelligence, namely artificial neural networks, to the prediction of the future development of a transport company. An example of the application thereof was carried out on a sample of transport and freight forwarding companies.

A search into the knowledge of the management of transport companies reveals that the utilizing neural networks to predict the future development of companies can be effective. However, real evidence was required from applying them to a particular group of transport and freight forwarding companies in the Czech Republic. An analysis of data was performed. The data was subsequently used for preparation of models. The model with the highest prediction accuracy was subsequently identified from among these models. With a classification accuracy of 94% we can conclude that the selected model is applicable in practice. To summarize:

1. Artificial intelligence was applied to the prediction of the future development of a transport company.
2. An example of the application was performed on a particular group of transport and freight forwarding companies.

The aim of this contribution was therefore achieved.

The results can be used not only in the academic environment for those teaching transport and logistics, but also by economists, for research purposes, and in practice.

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