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The application of Kohonen networks for identification of leaders in the trade sector in Czechia

JEL Classification: *C45; L60; M21*

Keywords: *trade sector; Kohonen networks; leaders in the field; cluster analysis; return on equity*

Abstract
Research background: The trade sector is considered to be the power of economy, in developing countries in particular. With regard to the Czech Republic, this field of the national economy constitutes the second most significant employer and, at the same time, the second most significant contributor to GNP. Apart from traditional methods of business analyzing and identifying leaders, artificial neural networks are widely used. These networks have become more popular in the field of economy, although their potential has yet to be fully exploited.
Purpose of the article: The aim of this article is to analyze the trade sector in the Czech Republic using Kohonen networks and to identify the leaders in this field.
Methods: The data set consists of complete financial statements of 11,604 enterprises that engaged in trade activities in the Czech Republic in 2016. The data set is subjected to cluster analysis using Kohonen networks. Individual clusters are subjected to the analysis of absolute indicators and return on equity which, apart from other, shows a special attraction of individual clusters

to potential investors. Average and absolute quantities of individual clusters are also analyzed, which means that the most successful clusters of enterprises in the trade sector are indicated.
Findings & Value added: The results show that a relatively small group of enter-prises enormously influences the development of the trade sector, including the whole economy. The results of analyzing 319 enterprises showed that it is possible to predict the future development of the trade sector. Nevertheless, it is also evident that the trade sector did not go well in 2016, which means that investments of owners are minimal.

Introduction

The trade sector is a very important area of the national economy in the Czech Republic. It is important to predict the future development of the sector. A certain group of companies influences not only the trade sector, but also the development of the whole national economy. Therefore, it is very important to identify sector leaders. Popular neural networks can be used to identify leaders, even if their potential has yet to be fully exploited. However, they have many advantages over conventional methods — they are flexible to use and capable of quickly and accurately analyzing complex data. Kohonen networks are a specific type of neural networks that can be used for data clustering, which will be crucial to achieving the aim of the article.

The aim of the article is to analyze the trade sector in the Czech Republic using Kohonen networks. The analysis will also identify the leaders in the sector.

The article will contain a literature review describing the importance of the trade sector with a focus on the Czech Republic and the specifics of artificial neural networks. This will be followed by a methodology that will include a description of the data used, methods and detailed analysis procedure. The next part will present the results of the research — analysis of average values and analysis of absolute indicators of individual clusters. This will be followed by a discussion and a final summary of the results.

Literature review

Every sector of national economy has its own specifications, which need to be defined (Balcerzak *et al*., 2017). The trade sector includes companies dealing with various types of products that are sold for the individual needs of customers, companies, and governments (Koh *et al*., 2016; Gavurová *et al*., 2017). Dyhdalewicz (2017) claims that these companies purchase a number of products, maintain their warehouses and deliver the products to customers. Doganay and Kocsoy (2011) state that the trade sector is regarded as a driving force of economy, especially in the developing countries.

Employees of the trade sector are one of the most important sources of competitive advantage. As this sector understands more than others how important the knowledge, skills and quality of the staff are, the significance of systematic and effective education grows (Lumpkin & Dess, 2005). The result of fast changes and increasing competitiveness of companies means that a design is becoming one of the key instruments of innovations and the key instrument of company performance (Abecassis-Moedas & Mahmoud-Jouini, 2008; Klieštik *et al*., 2018). The significance of trade has been emphasised within the Czech economy; the presented numbers have confirmed that trade is both the second most important employer and the contributor to the GDP. The independent trade sector accounts for more than 10% of the Czech economy. In 2014 the trade sector generated a 14% employment rate of the Czech GDP, i.e. the number of the trade sector employees is about 700,000.

The strategic vision of trade companies defines a Czech businessperson as an economic entity who relies on high quality and competitive products or services and innovative capacities, which are able to form new ideas and use the protection of intelligence property in a more efficient manner. They are able to apply the research knowledge and outputs which are generated by mainly domestic research organisations and are able to flexibly respond to the customers' requirements and turn them into the innovative products (Petrů *et al*., 2018). They apply the skills of effective Internet use and ICT, look for quality price advantages, succeed in the international markets and further extend both in terms of quality and quantity (Kramoliš *et al*., 2015).

Vochozka *et al*. (2018) claim that there are alternative methods for the company analysis and identification of leaders, e.g. neural networks (Kohonen networks). According to Smith (2000), neural networks are becoming increasingly popular in business. Many organisations are investing into solving problems by the means of neural networks. Artificial neural networks (ANNs) are widely used. The networks can be used in various fields and are becoming increasingly popular for the growing volume of data. There are many advantages in comparison with the regular methods, as they are flexible in terms of their use and are able to carry a fast and precise analysis of complicated patterns (Santin, 2008). Their main disadvantage is a procedure of optimization of the topology of hidden layers, which causes complications in the process of calculation as a result of high time consumption (Hossain *et al*., 2017).

Kohonen networks are a type of neural networks which can be used for clustering of data into separate groups. A Kohonen network learns by selforganization, i.e. without a teacher. It consists of an input layer, which is connected with the output layer (Šuleř, 2017).

Krulický (2019) claim that the Kohonen network can be applied in a wide range of cases as it is an alternative network applicable for the calculations of majority neural networks. These networks are very effective for an evaluation of companies, as it has been confirmed by many experimental results (Konečný & Trenz, 2010). Some authors, such as Machová and Vochozka (2019) analyse business subjects in the Czech Republic by means of neural networks and subsequently estimate the development in this part of the national economy. The analysis is carried out for the purpose of creation of a significant number of company clusters. An analysis of the most important clusters is carried out as well. The result can be generalised and it is possible to predict success or bankruptcy of companies. Therefore, it is possible to estimate both a total growth and decline of Czech trade companies, but also the structure of companies in terms of their size, turnover or revenue volume.

Vochozka (2017) analysed the companies in the manufacturing industry. The analysis was carried out by means of self-learning neural networks, i.e. Kohonen networks. Firstly, the individual clusters of manufacturing companies were identified. They were subsequently compared with each other. It was examined which clusters are essential for this sector, what annual performance they generate and what percentage of the whole sector it represents.

Research methodology

For the purposes of this contribution, a data set will be created which will include complete financial statements data of 11,604 companies operating in 2016 in the Czech Republic trade sector. These are business entities whose main activities are classified in Section G of the classification of economic activities CZ-NACE. The set of the companies will be generated from the Bisnode company Albertina database.

The data will be entered in Excel table. Each row will contain financial statements of one concrete company that will be identified by its name and identification number. The data set will not contain the data of the companies that did not perform their main activities during the entire monitored period. This applies to the companies that were CLOSED during the period (and thus did not have a significant influence on the national economy direction), and companies that commenced their activities during the period (and similarly did not have a significant influence on the direction of the Czech Republic — CR — trade sector).

The importance of the companies that started their business on 1 January 2016 and the companies that finished their activities on 31 December 2016 is debatable; however, it does not have a significant impact on achieving the objective of this contribution. The data columns that do not show any dispersion were excluded from the analysis. The data set will be subsequently subjected to cluster analysis using Kohonen networks. For the cluster analysis, Dell´s Statistica software, version 12 will be used. Moreover, the module Data mining and as a specific tool, Neural networks will be used. Here, the self-learning neural networks (Kohonen networks) will be used. The data for analysis will be determined by choosing an Excel table with a data set. In all the cases, these are continuous predictors. The data set will be divided into three parts:

1. Training data set: 70% of the companies in the data set. This data set will be used for creation of a network.
2. Testing data set: 15% of the companies in the initial data set. This data set will be used to verify the parameters of the created network.
3. Validation data set: 15% of the companies in the data set. This data set will be used to verify whether the created network is applicable or not.

Both the topological length and width of Kohonen network will be set at 10. The number of calculation repetitions (iteration) is set at 100,000. However, it should be noted that a decisive factor is the error level. If there is no improvement of Kohonen network parameters with every other iteration, the training will be finished before the 100,000th iteration is carried out. If the parameters improve even after finishing the 100,000th iteration, the entire process must be repeated with a higher number of iterations required in order to be sure that the result obtained is the best one possible. The training speed will be initially set at 0.1, in the end it will be 0.02. The results, that is, dividing the individual companies into clusters (100 in total) will be entered into an Excel table. Subsequently, the individual clusters will be subjected to the analysis of absolute indicators and return on equity. At this moment, it seems to be necessary to identify leaders in the sector. There are number of variables to be taken into account, including the following ones:

1. Volume of assets,
2. Volume of fixed assets,
3. Operating earnings,
4. Earnings before taxes.

Next, it must be determined whether we will try to find clusters that show extremely high absolute values of selected variables or cluster that show high average values. Within the analysis, we will examine both the average and absolute variables values of the individual clusters. This way, it will be possible to identify: 1. the most successful clusters in the trade sector, 2. the most successful companies in the trade sector. Return on equity indicates, inter alia, certain attractiveness of the individual clusters for potential investors.

Results

Figure 1 shows the number of companies in the individual clusters of Kohonen network.

The Kohonen network was calculated based on the assignment. In the text below, the network is referred to as SOFM 10–100. The companies were divided into clusters within a 10 x 10 topological grid. The frequency of the individual clusters is shown in Table 1. It results from the table that the highest number of companies in the individual field of the topological grid is in the position (1, 10), and (2, 10). Companies are less represented in (1, 9), (2, 9) and (2, 8). Generally, we can state that the highest number of the examined 11,604 companies are in (1, 7), (4, 7) and 1, 10), (4, 10). To get a detailed picture of the representation of companies in the individual clusters, Figure 1 was complemented by concrete values shown in Table 1.

The table shows that only the clusters marked red include more than 100 companies. The clusters containing more than 500 companies are marked yellow. Other clusters contain less than 100 companies. Further analysis will apply only to the clusters (1, 10), (2, 10), (1, 9), (2, 9), (2, 8), (4, 9), (3, 7) and (1, 7). They contain data on 5,905 companies, which accounts for 50% of the companies in the whole data set, although these are contained only in 8 clusters. Moreover, one of the clusters, namely (1, 10), contains 1,726 companies, which accounts for nearly 15% of the companies in the entire data set. Further analysis of the companies operating in the trade sector, or the analysis of the whole institutional sector of the national economy will be carried out from two perspectives:

1. Prism of the average values of companies in the individual clusters. This way it is possible to characterize the companies and determine to which extent are successful in their activities.
2. Absolute values for the individual clusters. This way it is possible to find out how the individual clusters influence the future development and success of the trade sector in the CR.

Analysis of average values

The first characteristic used is the fixed assets value for companies in the same cluster (Figure 2).

In practice, there is a marginal rate of substituting capital for work, i.e. fixed assets for workers. In the trade sector, though, work is irreplaceable (despite e.g. the cases of e-shops or sales by means of vending machines). Nevertheless, the fixed assets value indicates a lot about a company. It can be concluded that the company is active in terms of its real estates, uses its own means of transport, achieves a certain level of automation and uses quality software for its activities. Trade is a very specific industry. Trading companies as such do not create a value, except for offering additional services (e.g. packaging). The objective of trade is to mediate an exchange of a valuable company product to a customer. A product value indicates its ability to meet customers´ or consumers´ needs and requirements. Although trade does not create the product that could meet customers´ needs and requirements, its role is irreplaceable nowadays. A customer requires additional services and a certain culture of the exchange. Shopping in modern department stores or online and the time spent shopping become a part of modern people´s lifestyle.

The graph in Figure 2 shows that the highest average volumes of fixed assets are allocated in the companies of the cluster (10, 1). The second position is occupied by the clusters (8, 2), (9, 1) and (6, 3). The companies in the cluster (10, 1) own average fixed assets totalling more than CZK 690 million.

Besides fixed assets, an interesting indicator is also total assets of an average company in the individual clusters (Figure 3).

The volume of total assets predetermines a company ability to generate activities, i.e. realize the sale. It includes two of the three production factors [19] — fixed assets and material (goods in the case of trading companies). The third production factor starts to play role at the moment of consumption. The figure shows a high average of fixed assets in the clusters (10, 1), (10, 3) and (10, 2). A lower value, yet still very high, show the clusters (9, 1), (9, 3), (9, 2) and (8, 2). The companies in the most successful cluster show the average fixed assets value of CZK 106.5 million.

There are two other average values with great explanatory value — operating earnings and earnings before taxes.

Average operating earnings (Figure 4) enables to compare success of the companies in the individual clusters in terms of carrying out the main activities.

The highest average operating earnings is achieved by the companies in the cluster (8, 1) — nearly CZK 114 million. Less successful are the companies of the cluster (10, 2), generating average operating earnings of more than CZK 76 million. Then there are the clusters (10, 1), (10, 3) and (7, 1). Conversely, the companies of the cluster (10,4) generate an average loss of CZK 25.5 million. The last average variable analysed is earnings before taxes (see Figure 5).

Company earnings predetermine the success of the company in the investors´ eyes. For the purposes of the analysis, earnings before taxes were chosen, as the earnings are not distorted by taxation from the side of the company management. In this case, the highest value is not in the cluster (8, 1), but in the cluster (6, 9). Earnings before taxes of an average company in this cluster are nearly CZK 13 million. The cluster is followed by the companies in the clusters (10, 2) and (10, 3), showing the earnings before taxes at the amount of CZK 7.7 and 4.123 million. Conversely, the companies in the cluster (10, 10) reported a loss in 2016. The average loss was more than CZK 24.5 million per one company.

Analysis of absolute indicators

As already stated before, the analysis of absolute indicators indicates the importance of the individual company clusters for the CR trade sector. The same variables as in the case of the average values were analysed.

Figure 6 shows the absolute volume of fixed assets owned by the companies in the same cluster.

The figure shows that it is not possible to identify easily and unambiguously the clusters with the highest volume of assets, or rather that the differences between the clusters are not significant. However, when choosing the most important clusters in terms of the assets volume, the following order of the clusters will be obtained: (9, 1), (9, 4), (10, 5), (9, 5), (7, 1), (9, 8) and (9, 7). The data will be complemented by the information on the individual clusters share on the volume of owned assets (Figure 7).

The graph shows that the companies of the cluster (9, 1) own almost 2.63% of the assets in the trade sector. The companies in the cluster (9, 4) own 2.28% of all assets in the trade sector. Neither of the following clusters has a significant share of the institutional sector assets.

Another variable analysed was the fixed assets (see Figure 8).

The share of the individual clusters differs from the share of the total assets ownership. It is possible to identify two clusters with a significantly larger volume of fixed assets owned, namely (9, 1) and (10, 1). Other clusters owning a significant volume of fixed assets are the following ones: (7, 2), (6, 4), (8, 2), (3, 6), (4, 4), (6, 2) and (9, 10).

The situation will be better explained by relative comparison of the companies, i.e. the share on the total volume of fixed assets ownership in the trade sector (Figure 9).

The graph in Figure 9 indicates that the share of the companies in the cluster (9, 1) on the fixed assets ownership is 4.83%. The companies in the cluster (10, 1) hold 4.73% of the fixed assets in the trade sector. Another cluster owning more than 3% of the fixed assets is the cluster (7, 2). There are several clusters owning between 2 and 3% of the fixed assets in the trade sector; however, neither of the clusters can be considered important in terms of fixed assets ownership.

Figure 10 shows a comparison of absolute operating earnings. It is clear from the figure that the clusters with the largest volume of assets, or fixed assets, do not participate significantly in generating operating earnings. The most successful clusters include (7, 1), (3, 1), (7, 9), (3, 2), (8, 1) and (6, 10). Conversely, the worst results, a loss at the amount of CZK more than 960 million, were showed by the clusters (10, 6), and the cluster (3, 9) with a total loss of more than CZK 305 million. For detailed information, see Figure 11.

Figure 11 confirms the dominance of the cluster (7, 1). It generates 4.6% of the operating earnings of the entire trade sector. The second most successful cluster is (3, 1) generating 4.21% of the operating earnings for the entire trade sector. There are two more clusters, namely (7, 9) and (3, 2), exceeding a 3% share on the sector´s operating earnings. The remaining clusters do not participate significantly on the trade sector´s operating earnings.

The graph in Figure 12 shows data on the volume of earnings before taxes for the individual clusters.

It is very interesting that the clusters dominating the category of operating earnings do not generate appropriate earnings before taxes. It is thus obvious that the financial outturn and the extraordinary result must have been negative in the case of the companies, successful in their main activity. The earnings before taxes are thus mostly generated by the cluster (6, 9), generating nearly CZK 27.5 million of the earning before taxing the entire sector. The following important clusters were the clusters (10, 2) with nearly CZK 85 million and (5, 1) generating nearly CZK 48 million. This is also followed by the relative comparison of the values obtained (Figure 13).

The comparison shows that the cluster (6, 9) is essential in terms of earnings before taxes in the trade sector. It accounts for 32.58% of the earnings before taxes for the whole trade sector.

An important comparison is that of ROE for the individual clusters (for more details see Figure 14).

The graph shows that some clusters achieve extreme values, which are often out of rational range. These are, namely, the clusters (5, 10) with an extreme positive value and (10, 9) with extreme negative value. It was, therefore, necessary to set the ROE interval to be displayed in the graph. Figure 15 shows only the clusters whose ROE is in the interval between —100% and + 100%.

ROE (return on equity) provides information on the valuation of the owners´ deposit. It is considered one of the most important indicators of a company success. It is, by default, compared with the profitability of other investment opportunities in the market. The ROE disadvantage is that it does not take into account the risk of investment opportunities. The figure clearly shows the significant differences between the individual clusters. Despite the limited interval used for displaying the results, it must be stated that the clusters in the figure show very different values both in the positive and negative section of the interval. It is even not possible to identify the most and the least successful cluster. To identify them, it would be necessary to examine each one separately in order to find out whether the result is rational and whether it corresponds to the company´s possibilities. For example, negative earnings and negative equity indicate a positive ROE. The resulting value thus appears to be very positive. However, the result is not rational in the context. These are, of course, advantages of ration indicators in general.

Summary of the obtained results

It follows from the analyses carried out that the cluster (9, 1) is the most important one for the trade sector. This cluster contains 26 companies. However, it shows the highest absolute volume of assets and fixed assets. It also generates considerable operating earnings. An interesting fact is that its earnings before taxes is minimal and does not correspond to the value of the assets managed and the operating earnings generated. Still, it can be stated that the cluster (9, 1) is the most important cluster in the CR trade sector. It shall be recalled that in 2016, 11,604 companies operated in the trade sector. Taking into account all the analyses carried out, it can be concluded that the leaders in the sector are the companies in the clusters (9, 1), (7, 2), (9, 4), (9, 5), (9, 7), (9, 8), (10, 5) and (10, 3). However, their performance is not decisive in comparison with the performance of the entire sector. Table 2 shows an overview of the most successful clusters.

As trade sector leaders, 319 out of the 11,604 companies were identified. It accounts for 2.75% of all companies that were active in the sector in the monitored period. These 319 companies own 16.76% of all assets allocated in the trade sector. They also own 12.23% of all fixed assets in the trade sector. The 319 companies generate in total 12.81% of operating earnings of the whole trade sector, which is 12.6% of the earnings before taxes of the whole CR trade sector.

Discussion

Not many authors use neural networks to evaluate companies. Even fewer authors use the Kohonen networks and the classification of companies. The reason may be the complexity, where sorting into groups can be difficult even for experienced professionals. However, the literary research shows the clear benefit of Kohonen's networks, namely the fact that the classification is not burdened by a subjective view (Hang & Wang, 2018; Šuleř, 2017; Vochozka, 2017; Konečný *et al*., 2010).

Similarly, Konečný *et al.* (2010) used Kohonen networks in the Czech environment. They used the Kohonen network and financial indicators to classify a total of 80 agricultural companies. They declared the functionality and application of this method. Machová and Vochozka (2019), who analyzed trade companies in the Czech Republic using Kohonen networks, or Vochozka (2017), who analyzed manufacturing companies, followed a similar approach. The authors argue that the analysis can help the state to focus on supporting particular segments of companies with a view to their importance for the national economy.

We can certainly agree with this, but we still need to work with the results. In our article, we offer an analysis of a much larger data set and, in particular, a selection of industry leaders. This makes our contribution unique. It can be stated that this small group of companies has a high impact on the development of the trade sector. This statement can be considered a political implication. The analysis of industry leaders can have a positive impact on the whole industry and thus on the whole economy of the Czech Republic.

Conclusions

The objective of the contribution was to analyse the trade sector in the Czech Republic by means of Kohonen networks. The analysis also identified the leaders in the sector. The objective of the contribution was achieved. Using Kohonen networks, a cluster analysis was carried out. 11,604 companies operating in the trade sector in 2016 were divided into 100 clusters (Kohonen network was predefined using a 10 x 10 topological grid).

All clusters were subjected to analysis. The cluster with the highest representation of companies was the cluster (1, 10). The cluster, though, cannot be considered essential for the development of the CR trade sector. Conversely, the trade sector is influenced by the companies of the clusters (9, 1), (7, 2), (9, 4), (9, 5), (9, 7), (9, 8), (10, 5) and (10, 3). Although only 319 companies are in the clusters, the values of the average and the sum of the examined variables significantly exceed other companies operating in the trade sector. These companies thus can be considered the leaders in the sector.

It can be stated that this relatively small group of companies has a high impact on the development of the trade sector. This statement can be considered a political implication. Going further, we can also state that this group affects the development of the national economy. This is due to the nature of the activities of trading companies. Although trade does not necessarily create a value, its role in the national economy is irreplaceable. It mediates an exchange of products between companies and customers (consumers), thus enabling the division of labour at the level of the national economy. It can be concluded that the future development of the trade sector can be predicted based on the results of 319 companies.

Other companies, due to their number and small influence on the development of the sector, create a kind of breeding ground that will not change much in aggregate. However, as a tool for prediction, the analysis of 319 companies appears to be rather debatable. In addition, Kohonen networks can classify some enterprises in different clusters when re-calculating. It depends on the primary treatment of the data file. These are the limitations of the research. An advantage can be the fact that the development of the trade sector does not depend on several companies, but on a great number of them. Any fluctuation thus cannot be extreme.

Based on the analysis carried out, it must be stated that the trade sector was not in good condition in 2016. Valuation of the companies´ owners´ investment is minimal. The owners should thus consider allocations of their resources in other sectors with a higher valuation level than the risk-free return represented by ten-year bonds are.

Further research shall thus be focused on the following:

1. We should find out if the representation of companies in the individual clusters changes, especially in the clusters where the leaders in the sector come from.
2. We should verify the ability to predict the trade sector development based on the analysis of the leaders in the trade sector.
3. We should find out how potential fluctuation in the leaders´ results affected the development of the trade sector.

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Annex

Table 1. Number of companies in individual clusters of Kohonen map

	1	2	3	4	5	6	7	8	9	10
1	8	19	29	137	281	10	316	278	969	1726
2	29	24	45	88	150	26	151	446	636	1138
3	37	60	78	121	31	148	320	181	97	283
4	38	42	40	64	40	116	201	137	354	60
5	30	30	46	31	20	66	88	178	214	1
6	21	30	16	25	43	28	83	107	15	79
7	28	23	10	22	22	44	65	61	63	25
8	10	10	27	29	34	48	63	75	108	34
9	26	12	16	34	37	22	55	93	87	101
10	9	11	11	6	35	11	37	44	4	3

Table 2. Leaders in Czech trade sector in 2016

Clusters	Number of companies in cluster	Total assets	Fixed assets	Value added	Operating earnings	Earnings before taxes
(9, 1)	26	13,616,280	6,347,512	2,357,888	919,601	6,805
(7, 1)	28	10,381,961	2,036,349	3,715,884	1,762,623	0
(9, 4)	34	11,797,204	2,038,961	1,552,002	268,459	26,690
(9, 5)	37	10,749,514	858,137	752,458	75,975	0
(9, 7)	55	10,296,169	1,530,016	809,696	217,602	0
(9, 8)	93	10,340,779	1,311,452	1,990,623	681,028	1,935
(10, 5)	35	11,127,245	1,838,515	2,394,057	503,389	0
(10, 3)	11	8,318,644	111,298	1,081,062	480,051	44,805
In total	**319**	**86,627,796**	**16,072,240**	**14,653,670**	**4,908,728**	**80,235**
Share in trade sector	**2.75%**	**16.76%**	**12.23%**	**12.35%**	**12.81%**	**12.60%**

Figure 1. Number of companies in individual clusters of Kohonen network

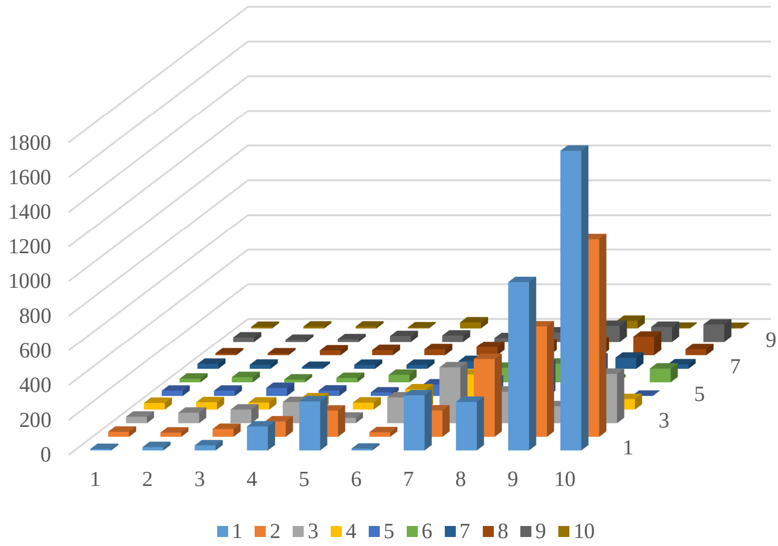

Figure 2. Average values of fixed assets for companies in individual clusters

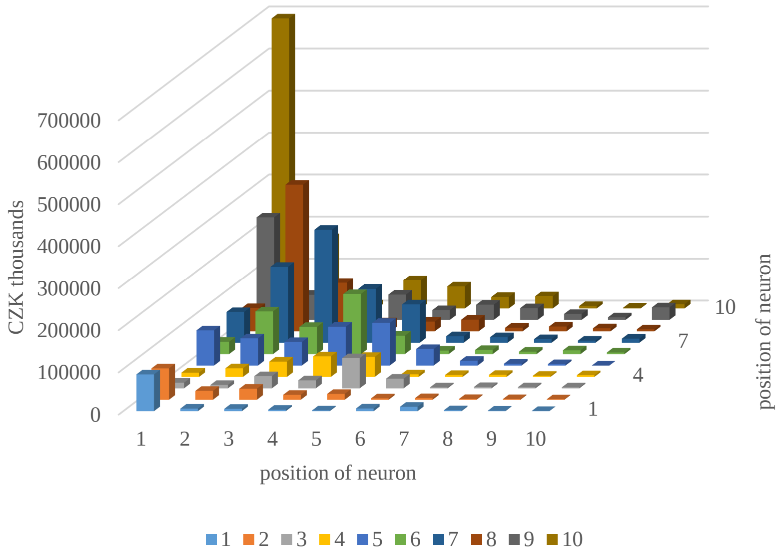

Figure 3. Average value of total assets for companies in individual clusters

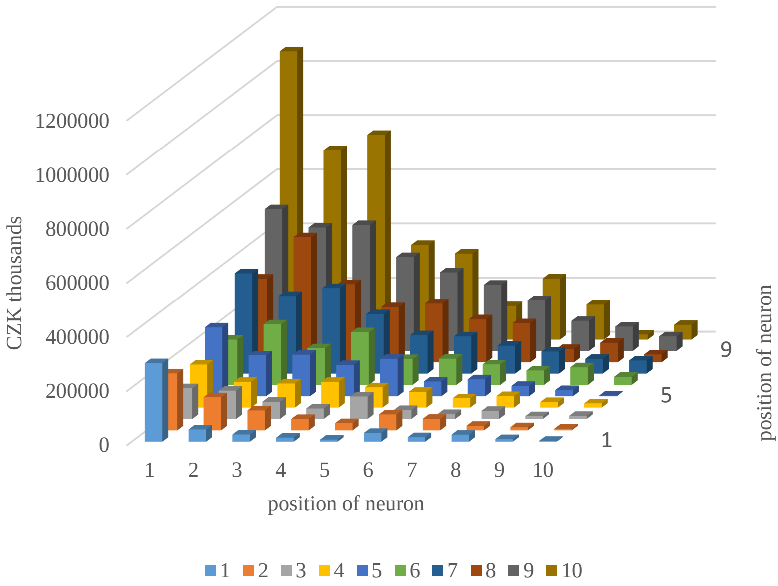

Figure 4. Average operating earnings of individual clusters

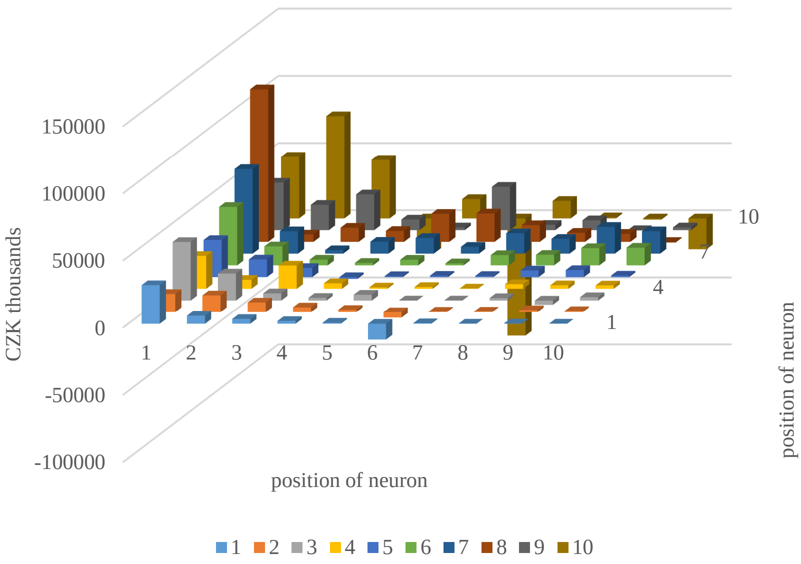

Figure 5. Average earnings before taxes for individual clusters

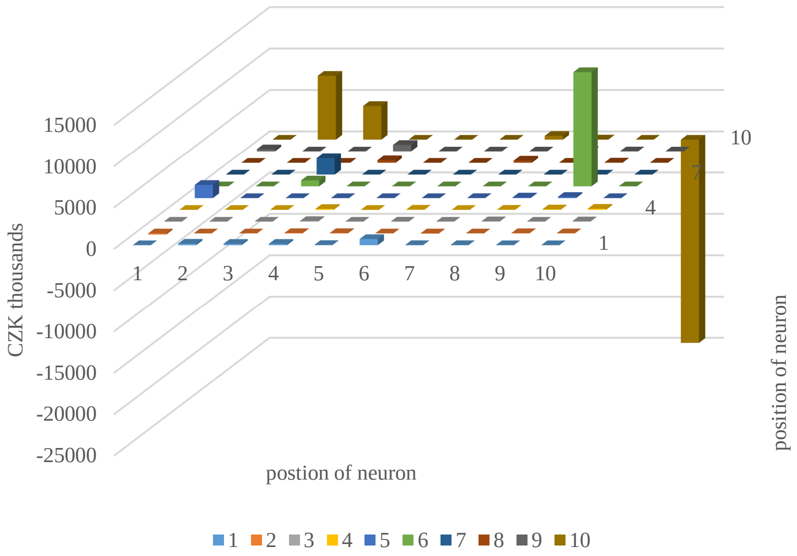

Figure 6. Volume of fixed assets owned by companies in the same clusters

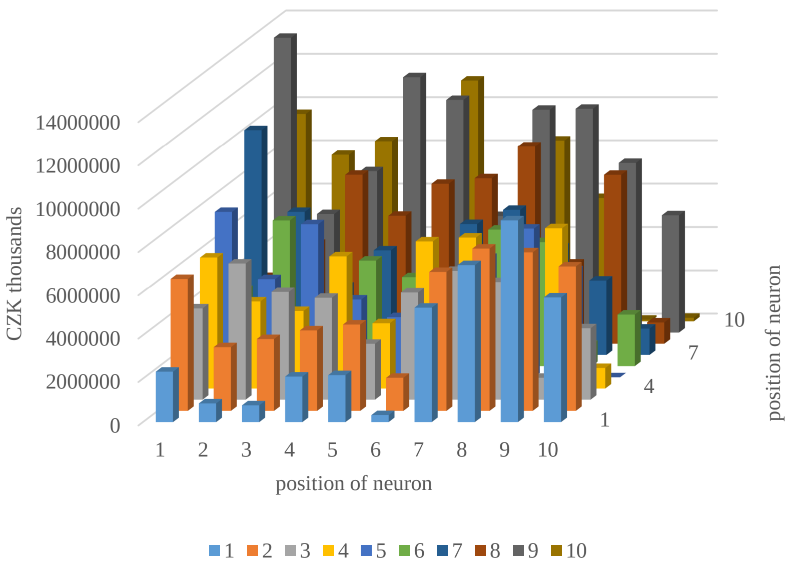

Figure 7. Share of individual clusters on owned assets in trade sector

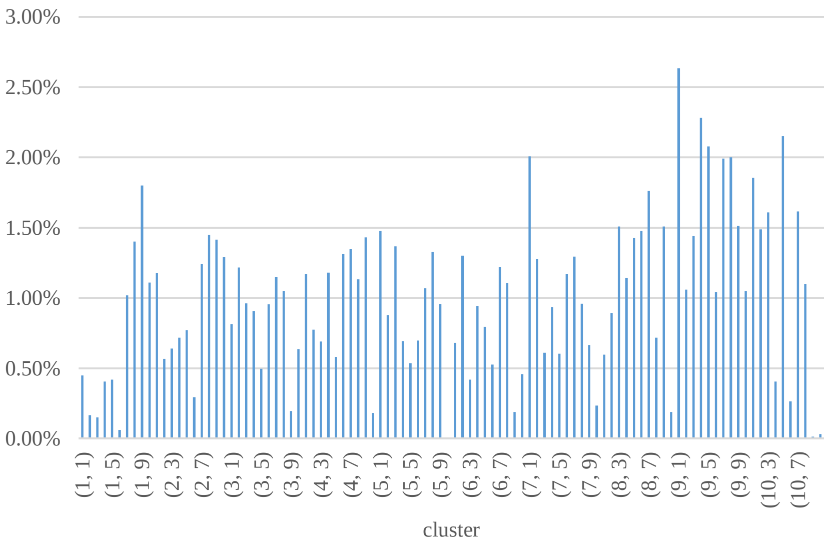

Figure 8. Amount of fixed assets owned by companies in the same clusters

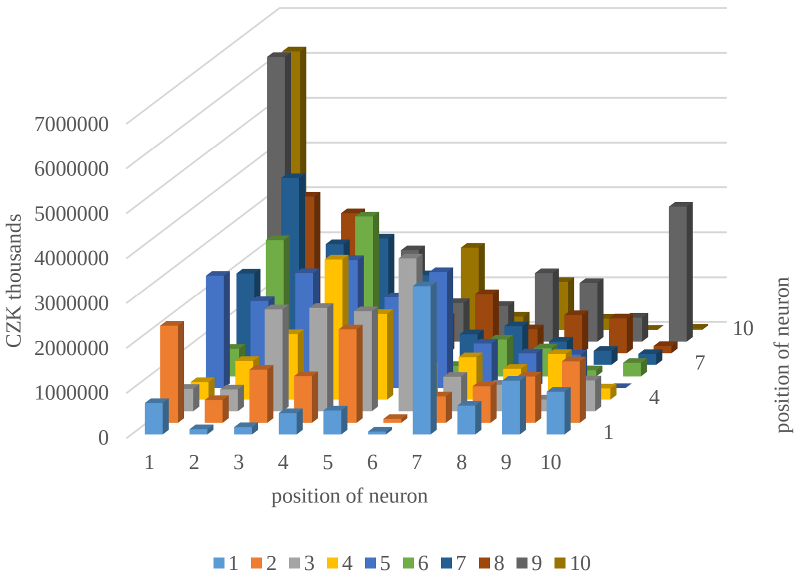

Figure 9. Share of individual clusters on fixed assets ownership in trade sector

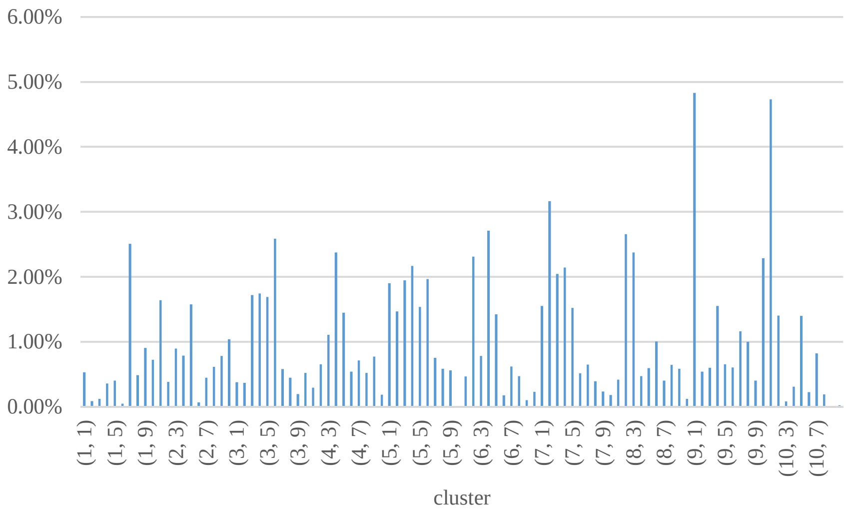

Figure 10. Volume of operating earnings for companies in the same clusters

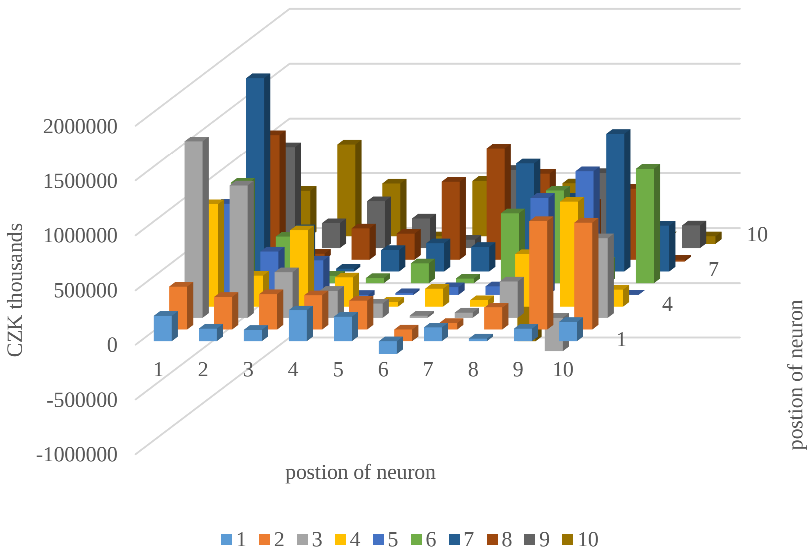

Figure 11. Share of individual clusters on the volume of operating earnings

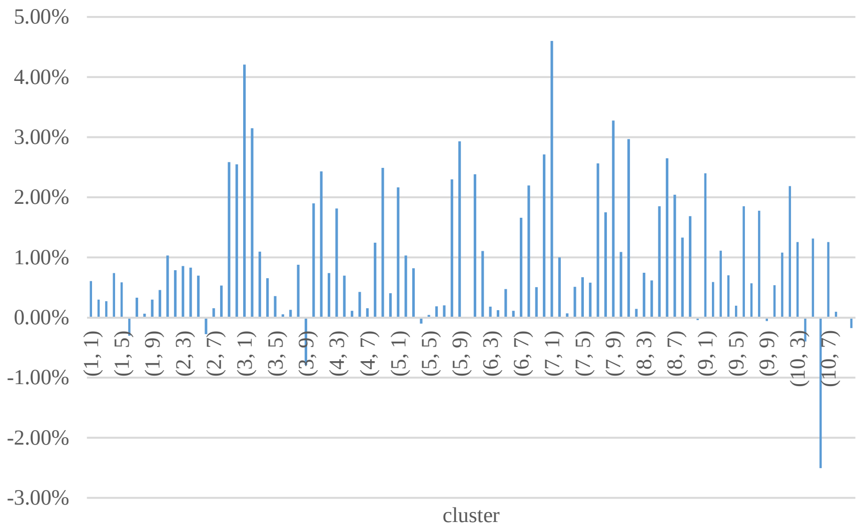

Figure 12. Volume of earnings before taxes for companies in the same clusters

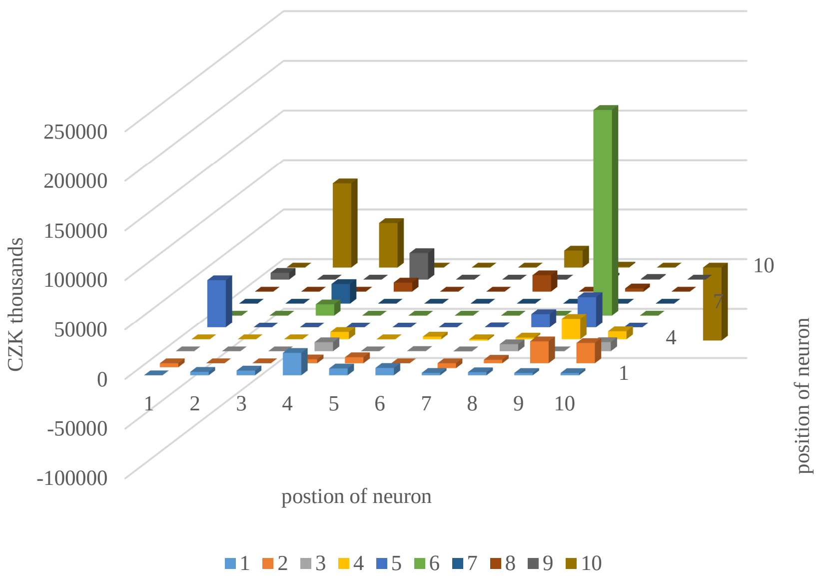

Figure 13. Share of individual clusters on earnings before taxes

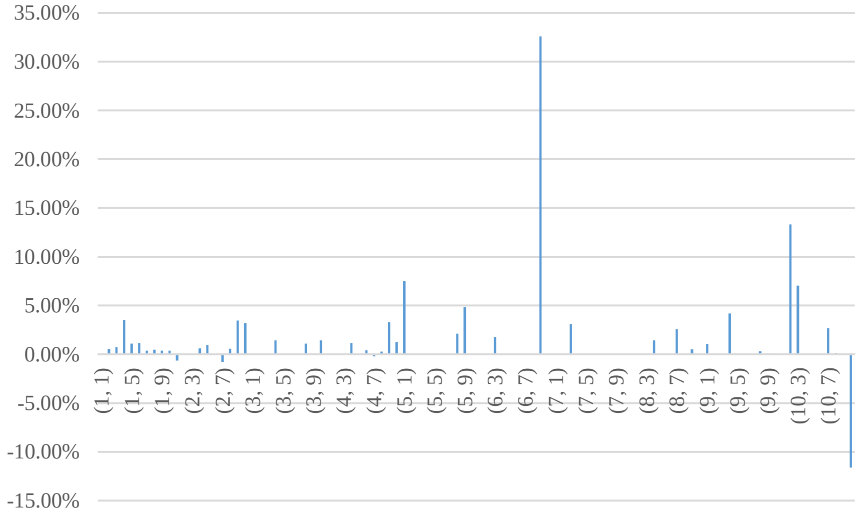

Figure 14. Comparison of ROE for individual clusters in trade sector

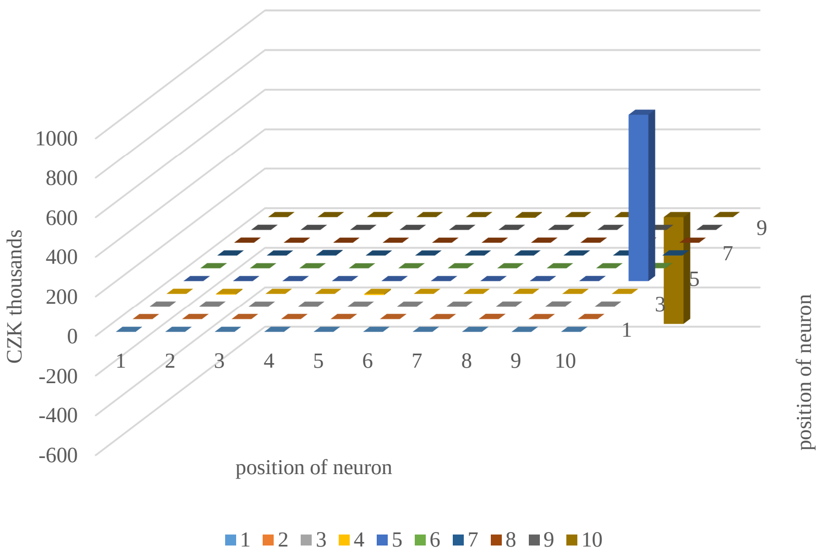

Figure 15. Comparison of ROE of the clusters achieving profit in the interval (-100; +100**)**