USE OF NEURAL NETWORKS FOR PREDICTING DEVELOPMENT OF USA EXPORT TO CHINA TAKING INTO ACCOUNT TIME SERIES SEASONALITY

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Abstract: The objective of the contribution is to propose a methodology of taking into consideration the seasonal fluctuations in time series equalization using artificial neural networks on the example of the United States of America export to the People´s Republic of China. For the research, the data from the period between January 1985 and August 2018 are used. For the prediction, two types of neural networks and two variants of input data sets are used. In the second variant, the seasonal fluctuation is represented by a categorical variable. It resulted that all retained structures are applicable, but the retained MLP networks of the B alternative achieve better results. It has been proven that with the use of artificial neural networks, it is possible to predict the export development efficiency and with a high degree of accuracy, especially in the short term and considering specific seasonal fluctuations.

Keywords: artificial neural networks; time series; export development; prediction; multilayer perceptron networks; radial basis function networks; seasonal fluctuations; United States; China.

1 Introduction

Artificial neural networks (ANNs) are compared with mixed conclusions in terms of the superiority in forecasting performance. However, the most researches indicate that deep-learning models automatically select highly abstracted features during the optimization process, and their representational power is better than that of traditional models. There is no output in the literature to compare neural networks with regression time series directly to export development. The objective of the contribution is to compare the performance and accuracy of equalizing time series by means of artificial neural networks on the example of the USA export to the PRC using two variants of the input data (A and B). Using the A variant, it is possible to predict the future development, while the B variant enables to predict the seasonal fluctuations. The objective is to show the possible uses and advantages of neural networks in practice.

The article offers the unique comparison of two variant ANNs, using the example of US exports to China. These are the two most important economies in the world today. The purpose is to see if ANNs are a better predictive tool when planning export. The resulting appreciation can help exporters to predict business development more effectively. This is appropriate at least to increase competitiveness.

2 Literature review

Until 1990, the USA exported the goods mainly to Western European countries (Zhang et al., 2017). Since 2013, China has been the third largest export market for the USA, after Canada and Mexico. However, the USA can trade with these two countries on land, without the necessity to use sea or air transport. In this respect, it can be said that China is the main overseas export market, also due to the fact that both the USA and China are the largest world economies that have maintained business relations with each other for a long time. According to Bernard and Jensen (2004), export is the most suitable way to ensure the economic growth of the state. According to the results of their research, export in exporting companies accounts for more than 40% of their productivity growth, which is very favorable in general.

Leightner (2018) reports that a USD 1 increase in China´s foreign exchange reserves resulted in the change in export in both states. The statistical method used creates a reduced estimate that capture the influence of neglected variables without the necessity of creating and estimating complex structural models. Moreover, he confirmed that there was acccumulation of China´s foreign exchange reserves at the amount of USD 621 million. This fact corresponds with the Chinese export change by USD 151 million and the USA export by USD 628 million. By contrast, in November 2016 China spent USD 69 bn from its foreign exchange reserves to support Yuan value, which corresponds with the China export increase by USD 4.77 bn and the USA export increase by USD 2.42 bn. According to Bahmani-Oskooee et al. (2013), there is a significant imbalance in the USA export to China between the individual industries. Chen (2014) reports that between 1997 and 2012, China became a world importer of goods.

According to Czech Statistical Office (2018), the USA export to China in 2017 amounted to USD 129.9 bn, which is a 12.4% increase (USD 14.3 bn) compared to 2016. In 2017, the USA export to China accounted for 8.4% of the total USA export. In that year, the USA export mostly comprised aircraft, machinery, cereals, seed grain, fruits. In the agriculture sector, the USA export to China in 2017 amounted to USD 20 bn. Such high exports ensure work for a large number of American citizens and also supports investment and overall economic growth. The USA exports more than 20% of its overall agricultural production (Fields et al., 2018). This makes the USA the world most important food and agricultural products exporter (Fields et al., 2018). There have been many studies concerning the demand for export and the impact of the USA export support programmes on various agricultural commodities in target destinations. Those studies dealt with measuring the efficiency of the USA support programmes of exporting meat and poultry products, fruits and vegetables, nuts, and tobacco (Onunkwo and Epperson, 2000). According to Koh et al. (2016), there is a permanent deficit in trade in goods and the trade surplus in the service sector is one of the basic characteristics of the USA international trade. As the USA is one of the world largest exporters of agricultural commodities, a surplus in agrarian trade is another constant phenomenon (Peppas and Yu, 2007).

The creativity of American companies and strong pressure American companies put on enforcement and regard of intellectual property rights´ shows most in the export of services that are protected by property rights, thanks to which the USA export amounts to approx. USD 130 bn. It is the second largest services export item after travel services. Other important services export items include transport and financial services (Ministry of Foreign Affairs, 2018). The USA services export to China in 2017 amounted to USD 57.6 bn, which is 4.9% (USD 2.7 bn) more than in 2016. The main services export from the USA to China include travelling, intellectual property (trade mark, computer software), and transport (Kalafsky and Graves, 2018). Geng et al. (2017) report that it is in the interest of both countries that their mutual financial flows are as close as possible and both economies thus could grow from export at the same pace. In their opinion, this is the only key to maintain business relations between these two nations.

The USA comparative advantage to China consists in producing high technologies and top-quality agricultural products. California, home to many technology companies, exports mobile phones electronics to China. Due to the location of the company Boeing, Washington is the USA largest exporter to China in terms of aviation. For comparison, China´s comparative advantage consists mostly in sophisticated industrial products (Urumov, 2015). Mostly due to the introduction of new mining technologies, the USA has become an important producer of petroleum and natural gas and its results are evident both in terms of the USA and the whole world (Jirušek and Vlček, 2017).

2.1 Using artificial neural networks models

To estimate the development of export, artificial neural networks (ANNs) can be used (Rowland and Vrbka, 2016). According to Vochozka, Horák and Šuleř (2019), neural networks have been widely used in more and more areas. However, according to

Fioretti (2014), their application in the economic sector is still in the early stage. Serrano Cinca (1996) dealt with using ANN in economics in 1996. The advantage of ANN consists mainly in their capability of working with big data and precision of their results (Vrbka and Rowland, 2017). According to Tealab (2018), the models of neural networks can be used for the approximation of the functions with high precision; they contain a hidden layer of neurons, which uses non-linear stimulation for predicting financial trends. A relevant import and export topic was addressed by Tsai and Huang (2017), who, among other goals, used ANNs for predicting utilization of selected Asian ports for import and export to and from the rest of the world. Alam (2019) dealt with the issue of import and export for Saudi Arabia. This was another example of using ANNs for predicting the development in this area of the state´s economy.

Import and export rate, together with other factors, can influence the economic growth of the state. Sokolov-Mladenovic et al. (2016) used ANNs for predicting the GDP growth on the basis of the country´s export and import rate. In this case, it was a connection of ANNs, back propagation learning, forward neural network, and extreme learning machine. Their research confirmed the reliability of predicting by means of this prediction model. Another very important way of using ANNs in the economic sector is the prediction of share price development using this method. In 2016, Qiu et al. (2016) tried to improve the prediction of share price development on the Japanese market by means of genetic algorithms (GA). By means of GA, they managed to increase the accuracy of the prediction and improve the ANN performance. Kotur and Zarkovic (2016) point out another advantage of ANNs, which is the prediction of certain commodities price in real time. After training, ANNs is able to modify the results of the predictions immediately after recording additional input data, both in the short and long term. De La Hoz and Lopez Polo (2017) investigated the application of ANNs for classification of individual companies into companies which are able to export and companies which are not. Their resulting ANNs have 85.7% prediction precision. According to them, company competitiveness grows with its export potential.

3 Data and methods

The underlying data was taken from the World Bank. For the purposes of the analysis, the data on the USA export to the Public Republic of China will be used. The time period for which the data are available: the monthly balance starting from 1st January 1985 to August 2018. It thus contains 404 input information. The unit is billions, US dollars. The data descriptive characteristics (minimum, maximum, average and standard deviation) are given in Table 1.

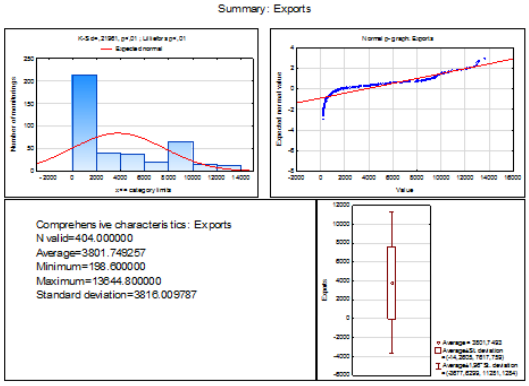
Tab. 1: Characteristics of data set

Characteristics	Month (Input variable)	Exports (Output – target)
Minimum (Training)	31,048.00	198.60
Maximum (Training)	43,313.00	13,644.80
Average (Training)	37,316.95	3,904.48
Standard deviation (Training)	3,549.13	3,818.51
Minimum (Testing)	31,138.00	198.80
Maximum (Testing)	42,948.00	12,598.60
Average (Testing)	36,651.48	3,503.40
Standard deviation (Testing)	3,758.45	4,015.30
Minimum (Validation)	31,199.00	212.70
Maximum (Validation)	42,979.00	13,147.80
Average (Validation)	37,060.87	3,613.85
Standard deviation (Validation)	5,186.49	3,289.34
Minimum (Overall)	31,048.00	198.60
Maximum (Overall)	43,313.00	13,644.80
Average (Overall)	37,180.08	3,801.75
Standard deviation (Overall)	3,554.16	3,816.01

Source: Own processing

What is interesting is the development of the USA export to the PRC over time. Figure 1 shows a graph of its statistical characteristics, including the histogram of the input data.

Figure 1: Graphs of basic statistical characteristics – summary



Source: Own processing.

For data and related information processing, DELL´s Statistica software (version 12), will be used.

ANNs will be used for regression problem. ANN is one of the computational models used in artificial intelligence. Its pattern is the behaviour of the corresponding biological structures. ANN is a structure designed for distributed parallel data processing. It consists of artificial (or also formal) neurons, whose biological model is a neuron. Neurons are interconnected and transmit signals to each other and transform them with certain transmission functions. Neuron has any number of inputs, but only one output. The general neural network model is described as follows:

$$Y = S(\sum_{i=1}^{N}(w_i x_i) + \theta) \quad (1)$$

where x_1 are neuron inputs, w_i are synaptic weights, θ is threshold, $S_{(x)}$ is the neuron transfer function (activation function), Y is a neuron output.

Out of curiosity, correlation coefficient has to be calculated, that is, the dependence of the export from the USA to the PRC on time. The significance level will be set of 0.95. Export directly depend on time because export has a clear trend over time.

Subsequently, regression analysis will be carried out using artificial neural networks. Multilayer perceptron networks (MLP) and radial basis function networks (RBF) will be generated. These are the two most widely used types of neural networks that software offers. MLP can be calculated by the formula:

$$y_k^n = f(w_{0,k}^n + \sum_{i=1}^{m} y_i^{n-1} * w_{i,k}^n) \quad (2)$$

The output of the k-th neuron located in the n-th hidden or output layer. $f(x)$ is the neuron transfer function, $w_{0,k}^{n}$ is the bias of the neuron and m is the number of weights of the neuron. RBF can be calculated by the formula:

$$f_k(x) = \sum_{j=1}^{k} w_i \varphi(|x - c_j|) \quad (3)$$

where c_j is point defining the center of $f_k(x)$ function, φ specifies a particular type or radial base function.

Two sets of ANN will be generated. In the first variant (variant A) an independent variable will be time. A dependent variable is the USA export to the PRC. In the B variant, continuous independent variable will be time. Seasonal fluctuations will be represented by categorical variable in the form of the month in which the value was measured. We will thus work with a possible monthly seasonality of the time series. In this variant, the dependent variable will be the USA export to the PRC. We will divide the time series into three data sets – training data set, testing data set and validation data set. The first group (training data set) will contain 70% of the input data. Artificial neural structures will be generated just based on the training data set. The remaining two data sets will contain 15% of the input data. Both mentioned data sets will be used for verification and evaluation of the generated artificial neural networks or final model reliability. We set the delay of the time series to 1. In total 10,000 artificial neural networks will be generated. Five artificial neural networks with the best characteristics will be retained in each input data variant. The method of least squares will be used. Generating of artificial neural networks will be finished when there is no improvement, i.e. when the sum of the squares isn´t lower. We will retain the artificial neural structures whose sum of the residual square compared to the actual development of the USA export to the PRC is as low as possible (zero in ideal case). As for the hidden layer, it will contain at least 2 neurons (50 at most). For the RBF, the hidden layer will contain at least 21 neurons (30 at most). For the MLP, the following distribution functions in the hidden layer and output layer will be considered: Linear, Logistic, Atanh, Exponential, Sinus.

Other settings will be left default (based on the ANS tool in Statistica software – automated neural structures).

Finally, the results of the linear regression method and regression carried out using artificial neural networks will be compared. The comparison will not be performed through residual analysis (minimum and maximum values, residuals dispersion, etc.), but at the level of expert view and experience of an evaluator (economist).

4 Results

4.1 Neural structures (variant A)

Based on the methodology, 10,000 ANNs were generated, out of which 5 with the best parameters were retained. Table 2 shows the overview of the ANNs with the best results.

Tab. 2: Overview of retained artificial neural networks

Network	Train. error	Test. error	Valid. error	Train. algorithm	Error function	Activation of hidden layer	Output activation function
RBF 1-28-1	216691	185586	121765	RBFT	Sum.quart	Gaussian	Identity
RBF 1-30-1	168459	212000	134165	RBFT	Sum.quart.	Gaussian	Identity
RBF 1-29-1	175555	174306	152127	RBFT	Sum.quart.	Gaussian	Identity
RBF 1-25-1	195090	246466	117514	RBFT	Sum.quart.	Gaussian	Identity
RBF 1-22-1	227256	190358	142195	RBFT	Sum.quart.	Gaussian	Identity

Source: Own processing

Table 2 shows that all retained ANNs with the best results are the radial basis function networks. The input layer contains only one variable (time). The hidden layer of the neural networks contains 22-30 neurons. The output layer can logically contain only one layer. This variable represents the USA export to the PRC. The training algorithm used for all networks was RBFT. Another interesting fact is identical functions in all retained networks, in the activation, output activation, and an error function. The hidden layer was activated by means of Gaussian curve, and the output activation function was Identity.

Another item to focus on in creating ANNs is training, testing, and validation performance. In this respect, the performance of the network shall ideally be the same in all data sets (here it shall be reminded that the distribution of the data into the data sets was random), and the error shall be as small as possible.

The performance of the individual data sets is in the form of correlation coefficient. The values of the individual data sets by specific neural networks are given in Table 3.

Tab. 3: Correlation coefficient of individual data sets

Network	Exports		
	Training performance	Testing performance	Validation performance
1.RBF 1-28-1	0.984921	0.988430	0.991039
2.RBF 1-30-1	0.988297	0.988281	0.989729
3.RBF 1-29-1	0.987801	0.989585	0.988935
4.RBF 1-25-1	0.986437	0.986660	0.991009
5.RBF 1-22-1	0.984181	0.988111	0.989333

Source: Own processing

It follows from Table 3 that the performance of all retained neural structures is approximately the same. The slight differences detected do not have any impact on the performance of the individual networks. The correlation coefficients of all training data sets range between 0.985 and 0.988 and higher. The value of the testing data sets correlation coefficient is not higher than 0.989. The correlation coefficient of all neural networks data sets is at most at the same level as the testing data set (namely 0.989). In order to choose the most appropriate neural structure, a more detailed analysis of the statistic results will be carried out. For this purpose, Table 4 showing the basic statistical characteristics of the individual data sets for all retained ANNs will be used.

Tab. 4: Statistics of individual data sets by retained artificial neural structures

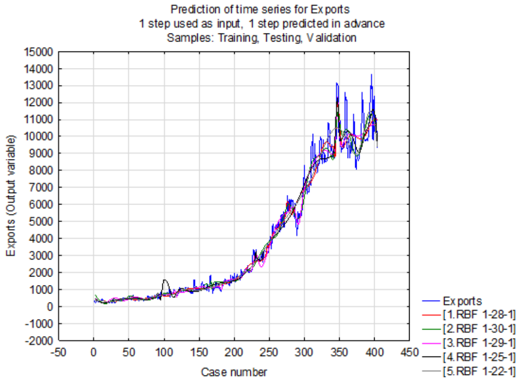
Statistics	1.RBF 1-28-1	2.RBF 1-30-1	3.RBF 1-29-1	4.RBF 1-25-1	5.RBF 1-22-1
Min. prediction (Training)	259.08	164.74	203.89	203.99	235.57
Max. prediction (Training)	11,934.48	11,480.75	12,282.35	12,244.18	11,475.85
Min. prediction (Testing)	257.66	251.68	247.16	255.62	242.91
Max. prediction (Testing)	10,517.86	11,204.47	10,544.19	10,745.98	11,420.62
Min. prediction (Validation)	258.04	338.23	327.32	309.83	277.61
Max. prediction (Validation)	11,594.45	11,264.07	11,894.33	11,960.48	11,467.61
Min. residuals (Training)	-1,954.55	-1,365.96	-1,960.51	-1,926.50	-1,907.18
Max. residuals (Training)	3,029.74	2,382.78	2,985.05	2,392.28	2,575.82
Min. residuals (Testing)	-1,171.46	-747.33	-948.16	-1,253.67	-973.47
Max. residua (Testing)	2,749.85	2,980.28	2,470.92	3,120.52	2,768.27
Min. residuals (Validation)	-1,801.24	-1,575.69	-1,840.77	-1,545.58	-1,382.05
Max. residuals (Validation)	1,553.35	2,098.92	1,347.50	1,187.32	2,642.57
Min. standard residua (Training)	-4.20	-3.33	-4.68	-4.36	-4.00
Max. standard residuals (Training)	6.51	5.81	7.12	5.42	5.40
Min. standard residuals (Testing)	-2.72	-1.62	-2.27	-2.53	-2.23
Max. standard residuals (Testing)	6.38	6.47	5.92	6.29	6.34
Min. standard residuals (Validation)	-5.16	-4.30	-4.72	-4.51	-3.67
Max. standard residuals (Validation)	4.45	5.73	3.45	3.46	7.01

Source: Own processing

In the ideal case the individual neural networks statistics are horizontally identical (minimum, maximum, residuals, etc.). In the case of equalized time series, the differences are minimal. However, the characteristics of the residuals show bigger differences. That is the reason why it is not possible to determine unambiguously, which of the retained neural networks shows the best results.

Figure 2 shows a line graph representing the actual development of the USA export to the PRC (blue curve) and the development of the predictions made by means of the individual generated and retained ANNS. The graph clearly shows that all the predictions of the retained neural networks predict the development of export in the individual intervals with a slight difference. However, in this contribution, we do not focus on the similarity of the individual ANNs´ predictions, but their similarity to the actual development of the USA export to the based on the actual statistical data. Even in this respect, it can be stated that all the retained neural networks appear to be interesting at first sight. All the curves of the graph representing the ANNs are similar to the "blue" curve representing the development of the USA export to the PRC. Another positive result is the retained ANNs´ ability to perceive the extremes of this curve (except for the cases at the end of the interval of the monitored period).

Figure 2: Development of USA export to PRC predicted using neural networks in comparison with the actual USA export to PRC in the monitored period



Source: Own processing

4.2 Neural structures (variant B) – seasonal fluctuations

Based on the second part of the methodology of predicting seasonal fluctuations using ANN, another set of 10,000 neural networks was generated, out of which 5 with the best parameters were retained. The overview of the retained networks is shown in Table 5.

Tab. 5: Retained neural networks

Network	Train. error	Test. error	Valid. error	Train. algorithms	Error function	Activation of hidden layer	Output activation function
MLP 13-27-1	103534	96823	114538	BFGS (Quasi-Newton) 101	Sum.sq.	Logistic	Logistic
MLP 13-25-1	103577	95125	113243	BFGS (Quasi-Newton) 92	Sum.sq.	Logistic	Exponential
MLP 13-10-1	103649	97540	113884	BFGS (Quasi-Newton) 58	Sum.sq.	Tanh	Logistic
MLP 13-4-1	109877	89753	113680	BFGS (Quasi-Newton) 50	Sum.sq.	Logistic	Exponential
MLP 13-33-1	103425	95558	113343	BFGS (Quasi-Newton) 127	Sum.sq.	Logistic	Exponential

Source: Own processing

In the second variant (variant B), only multilayer perceptron networks were retained. The hidden layers contain two variables – time (continuous variable) and the month of measurement (as a categorical variable). Time is represented by one neuron in the input layer, month by twelve neurons. The neural networks in the hidden layer contain 4-33 neurons. The output layer logically contains one neuron and one output variable, that is, the USA export to the PRC. For all networks, Quasi-Newton training algorithm was applied in various alternatives. Neural structures use logistics function and function of hyperbolic tangent function for activation of the hidden layer. Similarly, for the activation of the output neuron layers, two functions are used – exponential and logistics (for more details, see Table 5). As an error function, all the retained neural networks used the sum of the least squares.

The performance in the form of the individual data sets correlation coefficient by specific neural networks are given in Table 6.

Tab. 6: Correlation coefficients of individual data sets

Network	Exports		
	Training performance	Testing performance	Validation performance
1.MLP 13-27-1	0.992821	0.994509	0.991357
2.MLP 13-25-1	0.992818	0.994677	0.991424
3.MLP 13-10-1	0.992814	0.994450	0.991414
4.MLP 13-4-1	0.992381	0.994666	0.991482
5.MLP 13-33-1	0.992829	0.994599	0.991406

Source: Own processing.

It results from the table that the performance of all the retained neural structures is approximately the same. The slight differences detected do not have any influence on the performance of the individual networks. The value of all the training data sets correlation coefficient is more than 0.992 for all neural networks, and more than 0.994 in the case of testing data sets. The correlation coefficient of the validation data sets is above 0.991. To choose the most suitable neural structure, a detailed analysis of the results obtained must be carried out. Table 7 shows the basic statistical characteristics of the individual data sets for all neural structures.

Tab. 7: Statistics of individual data sets by retained neural structures

Statistics	1.MLP 13-27-1	2.MLP 13-25-1	3.MLP 13-10-1	4.MLP 13-4-1	5.MLP 13-33-1
Min. prediction (Training)	228.69	242.48	264.23	313.86	211.23
Max. prediction (Training)	13,159.82	13,045.01	13,088.70	13,189.25	13,013.82
Min. prediction (Testing)	260.56	257.35	299.48	312.40	232.12
Max. prediction (Testing)	12,954.08	12,986.06	12,901.94	12,885.57	12,947.81
Min. prediction (Validation)	264.83	280.65	324.25	330.96	282.77
Max. prediction (Validation)	11,603.57	11,772.44	11,677.18	11,396.74	11,771.35
Min. residuals (Training)	-2,221.94	-2,282.59	-2,242.37	-2,210.44	-2,245.79
Max. residuals (Training)	1,759.21	1,936.72	1,659.70	1,828.85	1,860.92
Min. residuals (Testing)	-1,402.62	-1,448.76	-1,398.97	-1,372.53	-1,414.98
Max. residuals (Testing)	935.45	967.88	891.31	906.74	880.73
Min. residuals (Validation)	-1,657.22	-1,761.22	-1,657.48	-1,386.87	-1,769.12
Max. residuals (Validation)	1,544.23	1,375.36	1,470.62	1,751.06	1,376.45
Min. standard residuals (Training)	-6.91	-7.09	-6.97	-6.67	-6.98
Max. standard residuals (Training)	5.47	6.02	5.16	5.52	5.79
Min. standard residuals	-4.51	-4.70	-4.48	-4.58	-4.58

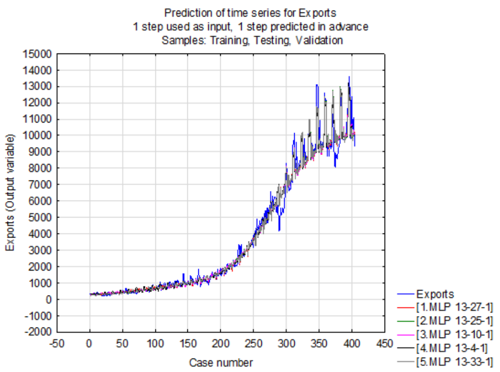
(Testing)					
Max. standard residuals (Testing)	3.01	3.14	2.85	3.03	2.85
Min. standard residuals (Validation)	-4.90	-5.23	-4.91	-4.11	-5.25
Max. standard residuals (Validation)	4.56	4.09	4.36	5.19	4.09

Source: Own processing.

In the ideal case, the individual statistics of neural networks are horizontally the same in all data sets (minimum, maximum, residuals, etc.). In the case of equalized time series, the differences are only small. There are minimal differences also in the case of the characteristics of the residuals. However, it is not able to determine unambiguously, which of the retained neural networks shows the best results.

Figure 3 is a line graph showing the actual development of the USA export to the PRC and the development of predictions by means of the individual generated and retained networks. It can be seen from the graph that all the neural networks predictions of the export development in the individual intervals are slightly different. However, what is important is not the similarity of the individual networks predictions, but the similarity (or degree of consistency) with the actual export development. All the retained neural networks predict not only the basic trend of the USA export to the PRC but also local minimums and maximum.

Figure 3: Line graph – development of USA export to PRC predicted by neural networks compared with actual export in monitored period



Source: Own processing.

Figure 3 clearly shows that all the retained multilayer perceptron networks can be applied.

5 Comparison of variants A and B neural structures – discussion

All generated and retained artificial neural structures in both variants were able to equalize the time series in question – the USA export to the PRC. The comparison of the correlation coefficients (see Tables 3 and 6) clearly shows a higher performance of the B variant, that is the retained MLP networks (with additional categorical variable). This shows also in evaluating the basic predictions statistics of the equalized time series in Tables 4 and 7. The retained MLP networks, or their equalized time series, show smaller differences in the training, testing, and validation data sets than the RBF networks (without additional variable). For confirmation, see Figures 2 and 3. It is evident that only the variant B MLP networks can capture the time series in its actual course. All the retained multilayer perceptron neural networks are able to capture all the course of the USA export to the PRC. All five multilayer perceptron networks are able to identify and retain the local fluctuations of the time series, that is, to capture its seasonal course.

6 Conclusion

The objective of the contribution was to propose a methodology of taking into account the seasonal fluctuations in equalizing time series using artificial neural networks on the example of the USA export to the People´s Republic of China with two variants of the input data.

Generally, each prediction is given by a certain probability degree of its fulfillment. In the case of predicting future development of any variable, we try to estimate its future development on the basis of the data available from past periods. A longer time data series from the past provides a basis for ANNs capable of more accurate prediction, including unexpected events. Even if most influencing factors of the target variable are included, the reality is always simplified and we always work with a certain degree of probability. This probability degree determines the degree of certainty that a certain scenario will be fulfilled. Both variants of the input data (variants A and B) of the ANNs represent a significant simplification of the problem being solved. In variant A, we worked only with two variables: time as an input variable, export (USA to PRC) as an output variable. Variant B included also a month in which the export data was obtained in order to determine and subsequently predict seasonal fluctuations in export. Although it appeared before the experiment that there is no reason to include categorical variable to capture the seasonal fluctuations from the USA to the PRC, the opposite was true. The additional variable included in the calculation in the variant B (in the form of the month of the measurement the export value) brought more order and precision in the equalized time series.

The USA export to the PRC can be determined on the basis of statistical methods, causal methods, and intuitive methods. In this case, two ANNs with different input data were compared. It is important to work with the information on the future development of the economic, political or legal environment. If we are able to predict their development, it can be included in the monitored variable. Here, the evaluator is important: an economist, who, on the basis of their knowledge and skills, is able to correct the price determined using statistical methods and specified based on the causal links. However, in this case, it appears it is only possible to test the prediction using the variant B, which brings quite a high degree of accuracy (all the retained neural networks).

The objective of the contribution was achieved.

An interesting fact is that in the case of the A variant, the retained structures were only the radial basis neural networks, while in the case of the b variant, these were only the multilayer perceptron neural networks. There could be an interesting experiment, if only one type of neural networks were generated for a given situation – a type different from the results already obtained (that is, MLP networks for the variant A and RBF networks for the variant B).

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Primary Paper Section: A

Secondary Paper Section: AH