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Comparison of Neural Networks and Regression time series in Predicting Development of EU Export to PRC

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Abstract

Purpose of the article This article focuses on the development of EU-China exports and trade in general, and also the advantages and disadvantages of regression analysis and neural networks in prediction.

Methodology/methods The data for the analysis are available at the World Bank websites, etc. For the purpose of the analysis, the data on the EU export to the People´s Republic of China (hereinafter referred to as "PRC") is used. The time-period for which the data are available is a monthly export for the period starting from January 2000 and ending in July 2018. In total, it is 223 input data. The unit is euro.

Scientific aim The objective of the contribution is to compare the accuracy of equalized time series by means of regression analysis and neural networks on the example of the EU export to the PRC.

Findings It can be stated that due to the high simplification of the reality it is not possible to predict extraordinary situations and their impact on the EU export to the PRC (at least not in the long term). Prediction in the order of days would be ideal; however, it is not possible to obtain data for such a short prediction.

Conclusions The EU export to the PRC can be identified based on statistical, causal and intuitive methods. These, however, provided only a possible framework of the monitored variable development. It is important to work with the information on a possible future development of political, economic or legal environment. Optically, in terms of the linear regression, the most suitable one appear to be the LOWESS curve. The second best possible is the curve obtained by the negative exponential smoothing least squares method and distance-weighting least squares method. In terms of neural networks, all retained neural structures appear to be applicable in practice, as there is no significant difference between them.

Keywords: neural networks, regression, time series, predicting development, export

JEL Classification: C22, C45

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Introduction

The PRC is now a trading accomplice with almost all nations since its opening up to international trade in the 1970's. Trade records between China and the EU is dated way back in the 1975 with the sole purpose of cooperating in strategic areas of improvement. Similarly, studies have proven that the EU import products from China more than the amount to which China imports from the EU. In 2001 China have become a member of the WTO and its membership have created a large effect on China's trade liberalization thereby leading to a decline of European's contribution to international trade from 37% to 31%, in conjunction with doubling of China's contribution from 5.5% to about 11% amid 2005 and 2015 (Karkanis, 2018).

Neural Networks and regression models were key studies subjects for over many years. Researchers over the years have had varying result in comparing neural networks and regression approaches. However, there is a famous call for in recent times for using neural networks in real time prediction because it requires less formal statistical training and it can implicitly detect complex non-linear relationships between dependent and independent variables.

1 Literature reviews

China´s export structure boom into the EU conforms to pattern of US tariff uncertainty (Mau, 2017). However, Goetz and Grethe (2010) highlighted that relevance of entry price system (EPS) has temporary nature for some product and a more general nature for some other products entering into the EU market from China. Accordingly, produces of fresh fruit and veggies from China benefit more from an improved market access in the EU.

Tao et al. (2018) explains that China's access to WTO in 2001 has spurred the growth of energy embodied in exports from China to the EU, at the same time as environmental policies issued by Chinese government since 2006 have pulled it down. The export sectoral shape changes and energy intake depth lower are key drivers of China's embodied power export modifications. Empirical result suggests that Chinese exports to EU have benefited from an unfair aggressive benefit through manipulation of its foreign money value (Cardoso and Duarte, 2017).

Karkanis (2018) applies a gravity model to asses elements underlying trade between China and EU for both export and import. His end result shows that the landlocked nature of several EU countries are useful for bilateral trade flow and other factors have brought positive contribution to EU-China bilateral trade expansion. Canofari and Ponte (2018) discovered that due to the increasing credit score gap in the Chinese economy and also the enduring political instability in some EU countries sent out a warning against the possibility of opening contagion channels between China and the EU. Trade and investment from China into the EU increased markedly in the years up to 2011, however fall since then, most notable for trade. Trade tensions and essential changes in the EU market explains some of the falls in trade between EU and China (Curran et al, 2017). Wang (2015) therefore emphasised an urgent need for the invention of new types of trade dialogues between China and EU as a necessary measure towards trade dispute settlement policy.

Gabriel (2008) expected an economically and politically reinforced China vis-a-vis the EU even as variations remain on the benefits losses relying at the ability of European nations to live united inside the EU. Delfa and Potvin (2016) concluded that neural networks provide more accurate and strong alternatives to regression approaches after performing direct comparison between neural networks and regressions by means of comparing their ability to predicts manual arm strength (MAS) same sets of development and validation MAS data. Merdun et al. (2005) on the other hand reported that regression performs insignificantly better than artificial neural networks (ANN) in their research. They further pointed out that ANN produces promising result in future research or application.

Tu (1996) highlighted a number of advantages of neural networks over regression models. Neural networks calls for less formal statistical education, implicitly locate complicated non-linear relationships between structured and impartial variables, and discover all possible interactions among predictable variables. However, they may be prone to overfitting, have black box nature, and create more computational burden as compare to regression models. Bilandzic et al. (2016) concluded that neural networks produce considerably higher classification accuracy of their model whilst incorporating all available variables. Vrbka and Rowland (2017) state that the preference of artificial neural networks is seen in relatively easy use for complex problems and forecast. This review focuses on the development of EU-China exports and trade in general, and also the advantages and disadvantages of regression analysis and neural networks in prediction.

Over the years, researchers have investigated and compared ANN and regression approaches using different data set. Some researchers found superior performance for neural network and others finding no overall difference and predicted performance. China exports more merchandise to Eurozone as compare to the EU exports to China. Due to an increase in Economic uncertainty in recent years EU-China trade is unhealthy as China benefits more from an unfair trade with the EU. Therefore, the need for new forms of trade dialogues between China and the EU as a necessary measure for a win-win trade corporation cannot be overemphasized.

The objective of the contribution is to compare the accuracy of equalized time series by means of regression analysis and neural networks on the example of the EU export to the PRC.

2 Data and methods

The data for the analysis are available at the World Bank websites, etc. For the purpose of the analysis, the data on the EU export to the PRC will be used. The time-period for which the data are available is a monthly export for the period starting from January 2000 and ending in July 2018. In total, it is 223 input data. The unit is euro. The data descriptive characteristics are given in Table 1.

Table 1 Data set characteristics

Samples	Month (Input variable)	Export in EUR (Output (target)
Minimum (Training)	36526.00	1.418156E+09
Maximum (Training)	43252.00	1.851767E+10
Mean (Training)	39916.52	8.475793E+09
Standard deviation (Training)	1949.82	4.793844E+09
Minimum (Testing)	36586.00	2.019653E+09
Maximum (Testing)	43282.00	1.778345E+10
Mean (Testing)	39702.30	8.020231E+09
Standard deviation (Testing)	2174.13	5.348653E+09
Minimum (Validation)	36951.00	2.296125E+09
Maximum (Validation)	43040.00	1.842305E+10
Mean (Validation)	40047.88	9.021341E+09
Standard deviation (Validation)	3096.16	6.655736E+09
Minimum (Overall)	36526.00	1.418156E+09
Maximum (Overall)	43282.00	1.851767E+10
Mean (Overall)	39904.26	8.489109E+09
Standard deviation (Overall)	1963.77	4.872391E+09

Source: Own processing

An important phenomenon is the development of the export over time. Figure 1 shows a graph of selected statistical characteristics, including the histogram of the input data.

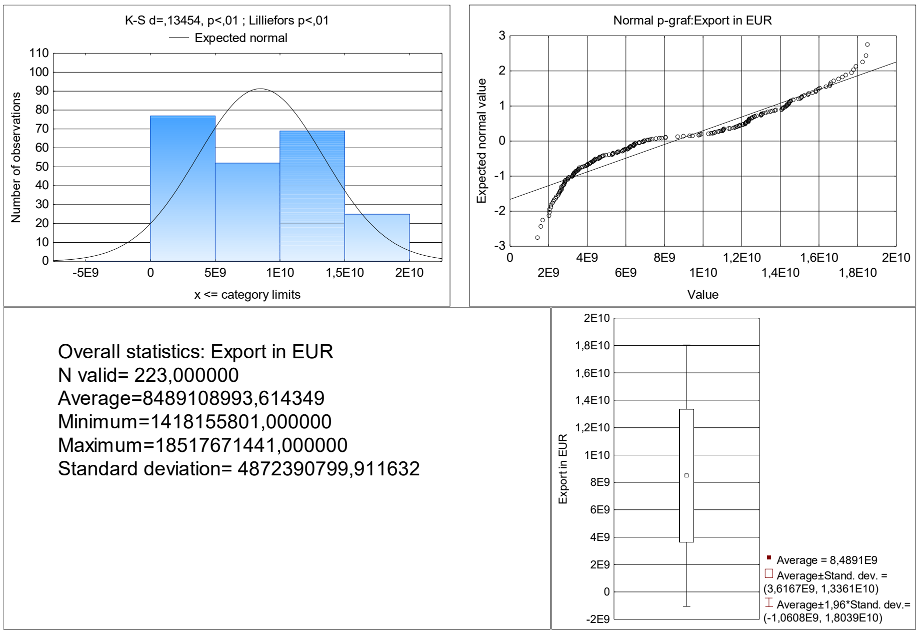

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Figure 1 Graph of basic statistical characteristics

The histogram indicates a higher data rate in the first three quartiles. For data processing, DELL´s Statistica software, version 12 will be used. Firstly, linear regression will be carried out. Subsequently, neural networks will be used for regression.

Linear regression will be carried out on the sample examined for the following functions: Linear, Polynomial, Logarithmic, Exponential, Distance weighting polynomial, Negative exponential smoothing polynomial.

First of all, correlation coefficient will be calculated, that is, the dependence of export on time. We will work with the significance level 0.95. Next, regression by means of neural structures will be carried out. We will generate multilayer perceptron networks and radial basis neural networks. The independent variable will be time, while the dependent variable will be the EU export to the PRC. The time series will be divided into three data sets - training, testing and validation. The first data set will contain 70% of the input data. Based on the training data set, neural structures will be generated. The two remaining data sets will contain 15% of the input data each. Both data sets will be used for verifying the reliability of the generated neural structure, or the model. The time series delay will be 1. In total, 10,000 neural networks will be generated, out of which 5 with the best characteristics. The hidden layer will contain at least 2 neurons (50 at most). In the case of radial basis function, the hid-den layer will contain at least 21 neurons (30 at most). For the multilayer perceptron network, the following distribution functions in the hidden and output layers will be considered: Linear, Logistic, Atanh, Exponential, Sinus.

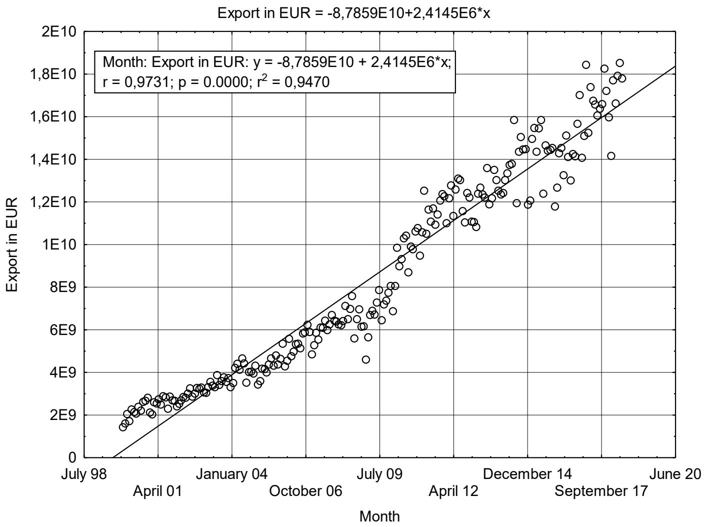
Other settings will remain default (according to the ANN tool – automated neural networks). Finally, the results of the linear regression and regression by means of neural networks will be compared. The comparison will not be carried out as a residuals analysis (minimum and maximum values, dispersion of residuals, etc.), but at the level of the expert view and experience of evaluator, an economist.

3 Results

3.1 Linear regression

The correlation coefficient is 0.9731, which is a statistically significant direct dependence of the export on the development over time. The determination coefficient has a value of 0.9470.

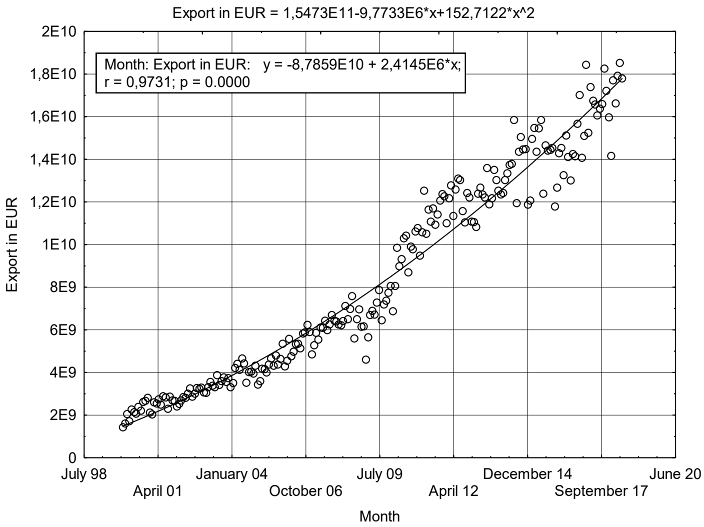
A scatter plot was designed (see Figure 2), where the individual points were fitted by the regression curve, linear in this case. The curve parameters are shown in the Figure.



Source: Own processing

Figure 2 Scatterplot showing EU export to PRC, with fitted regression curve – linear function

The solid line represents the regression function. At first sight, the curve captures the development of the monitored variable very well. Figure 3 shows a scatter plot with fitted polynomial function.



Source: Own processing

Figure 3 Scatter plot of EU export to PRC with fitted regression curve – polynomial function

Polynomial function captures the development of the EU export to the PRC slightly better than the linear function. Figure 4 shows a scatter plot with fitted logarithmic function.

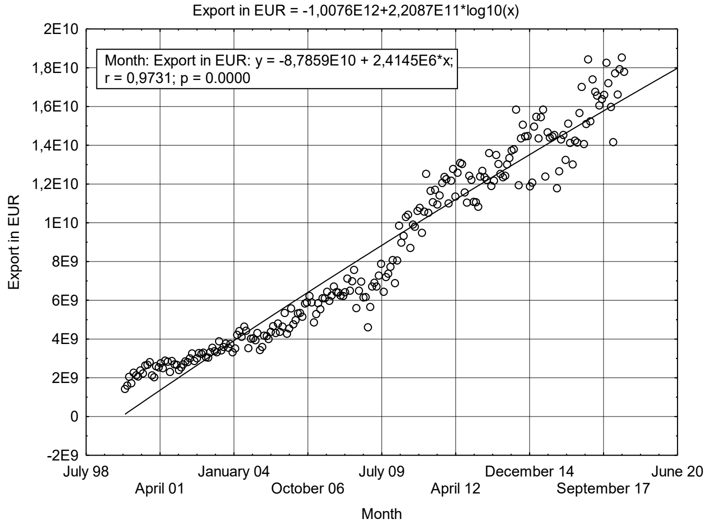


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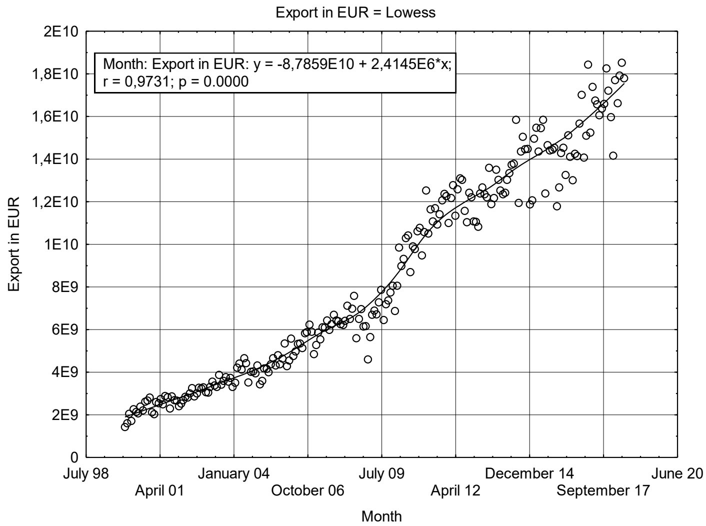
Figure 4 Scatter plot of EU export to PRC with fitted regression curve – logarithmic function

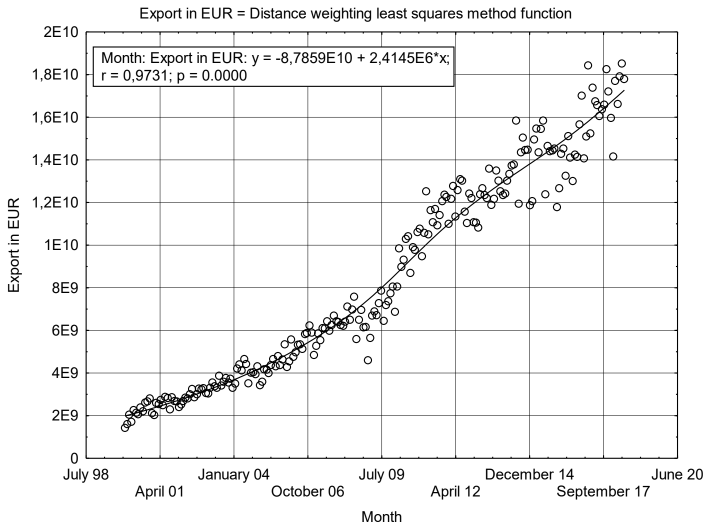
The shape of the curve and location of the individual points in the graph indicates that the logarithmic function replicates the linear function, thus predicting the development of the EU fairly well. Figure 5 represents LOWESS (locally weighted scatterplot smoothing), or LOES (locally estimated scatterplot smoothing) function.



Source: Own processing

Figure 5 Scatter plot of EU export to PRC with fitted regression curve – LOWESS

Regression for such a curve is calculated in partial intervals. The LOWESS curve equalizes the time series and follows its trend. Fitting by means of the LOWESS curve appears to be very interesting. It is able to predict the development trend of the EU export to the PRC. Figure 6 shows a scatter plot of the EU export to the PRC with fitted function obtained by means of the distance-weighting least squares method.



Source: Own processing

Figure 6 Scatter plot of EU export to PRC with fitted regression curve – distance weighting least squares method function

The curve replicates the development of the EU export to the PRC in its entire interval. However, it must be stated that in the detail, the curve is less precise than the previous LOWESS curve. Figure 7 shows fitting by means of function obtained by the negative exponential smoothing least squares method.

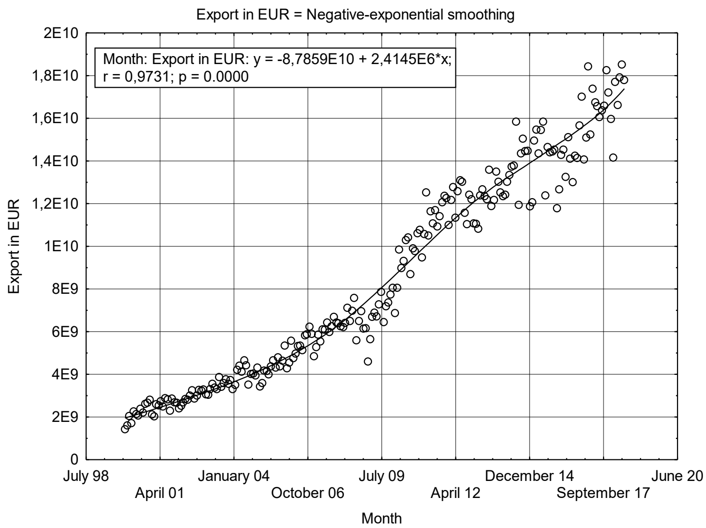


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Figure 7 Scatter plot of EU export to PRC with fitted regression function – negative exponential smoothing least squares method

This curve also appears to be interesting and suitable for a potential prediction. As already stated, the correlation coefficient indicates statistically significant direct dependence of the target variable on the development over time. The correlation coefficient is close to the limit value of 1. It can be stated that all created regression curves equalize the time series fairly well and at a certain level of accuracy, they show interesting results. If the results were assessed only based on the optical comparing of the EU export to the PRC and the regression curve shape, considering at the same time a simple linear regression, it could be stated that the LOWESS shows even better parameters. Other suitable curves are the curves obtained by the least squares methods, in particular by negative exponential smoothing and distance weighting. All of the three curves replicate the development of the EU export to the PRC.

3.2 Neural structures

Based on the aforementioned procedure, in total 10,000 neural structures were generated out of which 5 networks with the best parameters were retained. For their overview, see Table 2.

Table 2 Retained neural networks

	1	2	3	4	5
Network	RBF 1-26-1	RBF 1-29-1	RBF 1-29-1	RBF 1-24-1	RBF 1-25-1
Training perform.	0.988988	0.988831	0.988486	0.984297	0.983734
Testing perform.	0.985616	0.988322	0.988213	0.982806	0.987456
Validation perform.	0.986879	0.986892	0.987120	0.987108	0.987533
Training error	2.456164E+17	2.491079E+17	2.567633E+17	3.498046E+17	3.622694E+17
Testing error	4.005751E+17	3.249333E+17	3.356671E+17	4.809637E+17	3.572135E+17
Validation error	3.845149E+17	4.028760E+17	3.974787E+17	3.986220E+17	3.998826E+17
Training algorithm	RBFT	RBFT	RBFT	RBFT	RBFT
Error function	Sum.quart.	Sum.quart.	Sum.quart.	Sum.quart.	Sum.quart.
Activation of hidden layer	Gaussian	Gaussian	Gaussian	Gaussian	Gaussian
Output activation function	Identity	Identity	Identity	Identity	Identity

Source: Own processing

All of the retained networks are the radial basis neural networks. The input layer contains one variable only – time. The neural networks in the hidden layer contain between 24 and 29 neurons. The output layer logically contains only one neuron and one output variable – the EU export to the PRC. For all networks, RBFT training algorithm was applied. Moreover, all neural structures used the identical function for the activation of the neurons in the hidden layer, namely Gaussian function. Likewise, they use the same function for the activation of the neurons in the output layer, namely the identity function (for more details, see Table 2).

Training, testing and validation performance is also interesting. In general, we are looking for a network with ideally the same performance in all data sets (here it should be noted that the data were randomly divided into the data sets). At the same time, the error should be as small as possible. The performance of the individual data sets is expressed as a correlation coefficient. The values of the individual data sets by concrete neural networks are shown in Table 3.

Table 3 Correlation coefficients of individual data sets

	Exports (Training)	Exports (Testing)	Exports (Validation)
1.RBF 1-26-1	0.988988	0.985616	0.986879
2.RBF 1-29-1	0.988831	0.988322	0.986892
3.RBF 1-29-1	0.988486	0.988213	0.987120
4.RBF 1-24-1	0.984297	0.982806	0.987108
5.RBF 1-25-1	0.983734	0.987456	0.987533

Source: Own processing

It results from the table that the performance of all retained neural structures is nearly identical. The slight differences do not affect the performance of the individual networks. The value of all training data sets correlation coefficient ranges from almost 0.984 to more than 0.988. The value of testing data sets correlation coefficient is more than 0.982 for all neural networks. The validation data set correlation coefficient for all neural networks is above 0.986. To choose the most suitable neural structure, a more detailed analysis of the results obtained must be carried out. Table 4 shows the basic statistical characteristics of the individual data sets for all neural structures.

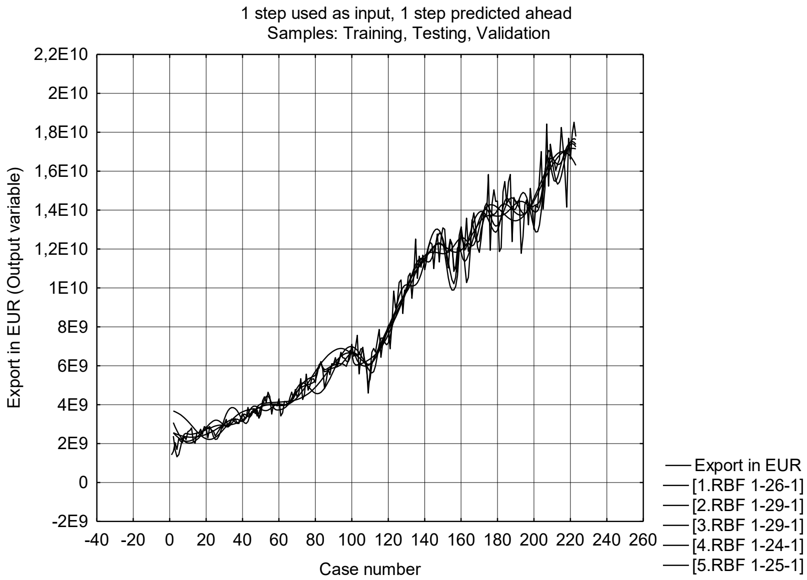
Table 4 Statistics of individual data sets by retained neural structures

Statistics	1.RBF 1-26-1	2.RBF 1-29-1	3.RBF 1-29-1	4.RBF 1-24-1	5.RBF 1-25-1
Minimal prediction (Training)	1.324366E+09	2.330010E+09	2.122872E+09	2.024698E+09	2.214571E+09
Maximal prediction (Training)	1.741536E+10	1.752462E+10	1.700726E+10	1.767183E+10	1.717502E+10
Minimal prediction (Testing)	1.431736E+09	2.339535E+09	2.271759E+09	2.141664E+09	2.264442E+09
Maximal prediction (Testing)	1.736600E+10	1.749158E+10	1.696743E+10	1.762770E+10	1.716703E+10
Minimal prediction (Validation)	2.536782E+09	2.351635E+09	2.344404E+09	2.214503E+09	2.220246E+09
Maximal prediction (Validation)	1.646363E+10	1.655168E+10	1.700041E+10	1.670868E+10	1.690947E+10
Minimal residuals (Training)	-2.920427E+09	-3.081541E+09	-2.784484E+09	-2.827718E+09	-2.955660E+09
Maximal residuals (Training)	2.472351E+09	2.274404E+09	2.300036E+09	3.070099E+09	3.311586E+09

Source: Own processing

Ideally, the individual statistics of the neural networks match horizontally in all data sets (minimum, maximum, residuals etc.). In the case of equalized time series, the differences in terms of individual variables are minimal. It is therefore not possible to identify which of the retained neural networks shows the best results.

Figure 8 shows a line graph representing the actual development of the EU export to the PRC and the development of predictions by means of individual generated and retained networks. It results from the graph that all the neural networks´ predictions are slightly different in individual intervals. However, the important fact is not the similarity of the individual networks predictions, but their similarity (or degree of conformity) with the actual development of the variable monitored. Based on the optical comparison of the individual curves trend it can be stated, that all the retained neural networks follow the gradient of the curve representing the development of the EU export to the PRC and also perceive the extremes of the curve.



Source: Own processing

Figure 8 Line graph – development of EU export to PRC predicted by neural networks compared with actual export in monitored period

4 Discussion and conclusion

The objective of the contribution was to compare the accuracy of equalizing time series by means of regression analysis and neural networks on the example of the EU export to the PRC.

Generally, each prediction is given by a certain degree of probability of its fulfilment. To predict a future development of any variable means to try to estimate its future development based on the data from the previous periods. Although we are able to include most of the factors influencing the target variable in the model, there is always a certain simplification of the reality; we thus always work with a certain degree of probability that the scenario predicted will come true.

At the same time, it must be stated that the correlation coefficient is not equal to the degree of probability that a specific phenomenon will occur. It is only a mathematical variable evaluating a relation of two or more variables generated in the past, and we try to predict the future development analogically to the development in the past. Both, in the case of the linear regression and regression by means of neural networks, the reality is significantly simplified. We work with two variables only: input (time) and output (the EU export to the PRC). We thus do not consider any other input variables that often significantly affect the EU export to the PRC (international political situation, taxation in both countries, production factors price, government export subsidies, promotion of entrepreneurship, living standards of the target country inhabitants and many others). However, it is still true that aggregated variables are easier to predict than sub-variables. There-fore, for some analyses, it is possible to use regression by means of neural networks, which show higher accuracy.

At the same time, it can be stated that due to the high simplification of the reality it is not possible to predict extraordinary situations and their impact on the EU export to the PRC (at least not in the long term). Prediction in the order of days would be ideal; however, it is not possible to obtain data for such a short prediction. The EU export to the PRC can be identified based on statistical, causal and intuitive methods. In this case, we dealt with the comparison of the statistical methods. These, however, provided only a possible framework of the monitored variable development. It is important to work with the information on a possible future development of political, economic or legal environment. If we are able to predict its development, it can later be considered in the monitored variable. Nevertheless, it is also important the evaluator – economist, who, on the basis of his or her experience and knowledge, corrects the price determined by means of statistical methods and specified based on the causal links.

Optically, in terms of the linear regression, the most suitable one appeared to be the LOWESS curve. The second best possible was the curve obtained by the negative exponential smoothing least squares method and distance-weighting least squares method. In terms of neural networks, all retained neural structures appeared to be applicable in practice, as there was no significant difference between them. The objective of the contribution has been achieved. Due to the actual trend of the EU export to the PRC, it is possible to investigate predicting future developments taking into account seasonal fluctuations.

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