Comparison of neural networks and regression time series on forecasting development of US imports from the PRC

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Abstract

The contribution deals primarily with the development and prediction of the PRC export to the USA, comparing traditional statistical methods in the form of regression analysis of time series and artificial neural networks, which are a very important prediction tools, and become an integral part of modelling and predicting certain development of time series based on the statistical data. The USA import from China can be defined based on the statistical, causal, and intuitive methods. In this case, the contribution deals primarily with comparing the statistical methods. The contribution provides only a possible framework of the monitored variable development. It is necessary to work also with the information about the future economic, political or legal environment. If it is possible to predict their development, it can then be reflected in the monitored variable. Optically, the best option from linear regression appears to the curve obtained by the least squares method by negative exponential smoothing. As for the neural networks, all retained structures appear to be applicable in practice. In terms of the correlation coefficient, only neural networks are applicable.

Keywords: regression time series, neural networks, prediction, import.

Introduction

Import development and forecast may be determined based on statistical, causal and intuitive methods. In this case, the paper is focused on a specific comparison of statistical methods using the method of artificial neural networks, which has brought some promising results in similar applications recently. It consists in an artificial intelligence approach that, based on historical data, is able to accurately model and predict certain development of a time series. Therefore, the main objective here is to compare the accuracy of time series alignment using regression analysis and neural networks in terms of US imports from the PRC. Such imports were selected due to the enormous influence of the two countries on the world economy. Accurate measurements and adequate import forecasts may have a major impact on the world economy.

International trade may be characterized as the exchange of goods, services and capital across international borders. It represents a substantial share of gross domestic product in most countries (Fürst and Pleschová, 2010). Bernard (2004) states that the international, social, economic and political importance of international trade has been increasing in recent centuries. Also, international trade is a more complex process than domestic trade.

Rowland and Vrbka (2016) claim that in order to forecast import development, it is possible to use, for instance, artificial neural networks or regression time series. According to Sanchéz and Melin (2015), neural networks are widely applied in a number of different areas. The main advantages include, e.g. their ability to work with large amounts of data, the accuracy of results, etc. (Vrbka and Rowland, 2017; Šuleř, 2017). Sayadi et al. (2012) argue that other advantages of neural network methods for forecasting key business indicators involve the ability to learn and generalize. Neural network models may also be used to approximate high-precision functions (Tealab, 2018; Pao, 2008). Falat and Pancitova (2015) combined various models of state-of-the-art artificial neural networks and introduced an alternative in developing accurate forecasts of various financial factors. The precision of their technique gave the impression that it was on a comparable scale with standard models. When using regression in forecasting, time series ought to be considered while trying to forecast the future (Sloboda, 2015). According to Horák and Krulický (2018), there may be certain issues with time series data. On using time series regression models, it is important to distinguish two different types of forecasts, i.e. ex-ante and ex-post. The former is carried out only with previously available information, while the latter is created using subsequent information on predictors.

Literature research

The regression time series method enables to forecast a future response that is based on the response history and transmission of dynamics from relevant predictors. Additionally, regression time series allows to understand and forecast the behaviour of dynamic systems from experimental or observational data and at present, it is commonly used to forecast and model biological, financial and economic systems (Pesaran and Smith, 2014).

Imports from China to the United States require a large number of units being synchronized, keeping the supply chain in motion, and including several basic guidelines. The process also involves delivery of goods, payment for goods, transportation, ultimate distribution, etc. (Geng et al., 2017).

Ziyadin et al (2017) deal with China's current economic potential. China is one of the largest recipients of foreign direct investment in the world and plays a leading role in world trade.

Kourentzes (2013) designed a neural network methodology for forecasting intermittent time series used to provide dynamic demand forecasts not assuming a constant level of demand in the future and being able to capture interactions between non-zero demand and the rate of incoming demand. These neural networks have proven effective for intermittent demand applications.

According to Liu et al. (2009), CNY exchange rates may be considered as time series characterized by high uncertainty, non-linearity and time-varying behaviour. GBP-CNY and USD-CNY exchange rate forecasts were made with the use of RBF neural networks. A detailed design of RBF neural network architecture, transfer functions of hidden-layer nodes, input vectors and output vectors was put into practice by a number of tests. Experimental results showed that the performance of RBF neural networks for CNY exchange rate forecasts is acceptable and effective.

Dongdong and Wenhong (2011) note that financial time series is non-stationary, non-linear, and stochastic, which may prove to be difficult. The authors used a specific method based on wavelet analysis and artificial intelligence to forecast the A300 index in China and the NASDAQ index in the USA. Compared to the wavelet-ARIMA model and a simple BP neural network, their model shows superiority in performance forecasting. Results of different forecast lengths indicate that these methods are only suitable for short-term forecasts. The forecasting difference between the A300 and the NASDAQ suggests that the Chinese stock market is less efficient than the US one.

De Souza et al. (2010) introduced a new weight predictor of neural network time series that utilizes a virtual generalized Random Access Memory weight neural network to anticipate future returns of shares. The new predictor was evaluated on forecasting future weekly returns of 46 shares from the Brazilian stock market. Their results showed that the Random Access Memory weight neural network predictors are able to give forecasts of future returns with the same error levels and characteristics of basic predictors of autoregressive neural networks yet running 5000 times faster.

In January 2017, US imports from China rose from USD 39,381.80 billion to USD 41,376.30 billion, averaging USD 12,888.43 billion between 1980 and 2017 (with a record high of USD 45,700.60 million in September 2017 and a record low of USD 58.40 in March 1980) (Trading Economics, 2019). The highest import categories in 2017 were: electrical machines (USD 147 billion), machines (USD 110 billion), furniture and linen (USD 32 billion), toys and sports equipment (USD 26 billion), and plastics (USD 16 billion).

Methods and Data

The data for the analysis is available on the World Bank web pages, etc. The information about the import from China to the USA will be used for the purpose of analysis. The time interval covering the available data is a monthly balance, which starts in January 1985 and ends in August 2018. There are 404 input data. The unit is a billion of US dollars.

The descriptive data characteristics are shown in Table 1.

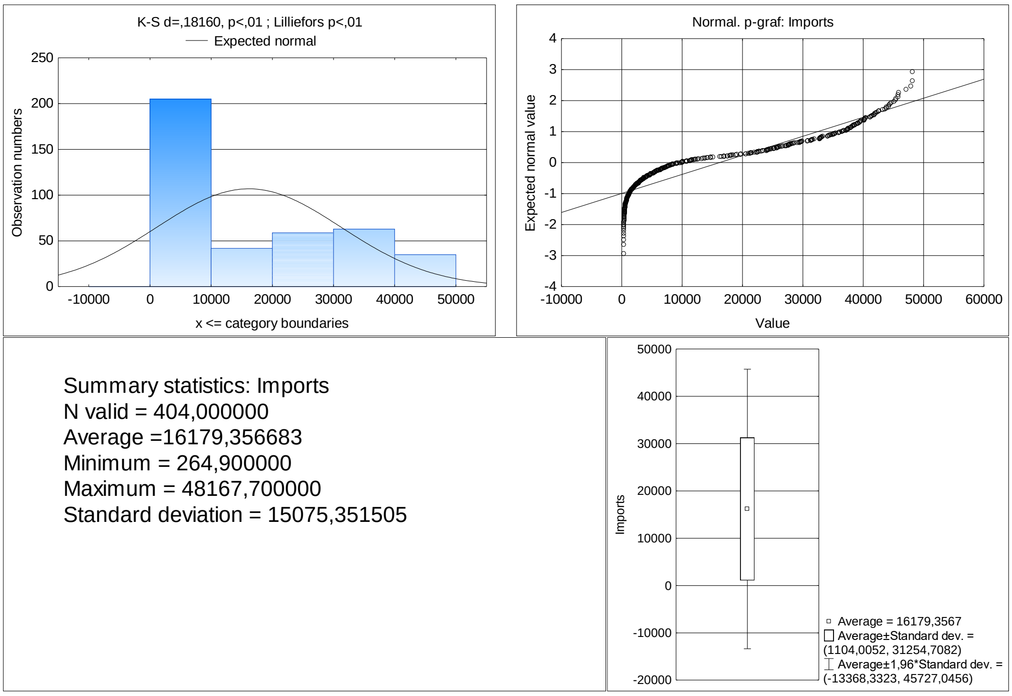
Tab. 1: The characteristics of data set

Samples	**Month (Input prom.)**	**Imports (Output (aim)**
Minimum (Training)	31,048.00	264.90
Maximum (Training)	43,313.00	48,167.70
Mean (Training)	37,316.95	16,718.52
Standard deviation (Training)	3,549.13	14,981.52
Minimum (Testing)	31,138.00	283.30
Maximum (Testing)	42,948.00	45,817.80
Mean (Testing)	36,651.48	14,618.18
Standard deviation (Testing)	3,758.45	16,187.18
Minimum (Validation)	31,199.00	348.70
Maximum (Validation)	42,979.00	45,429.70
Mean (Validation)	37,060.87	15,188.48
Standard deviation (Validation)	5,186.49	14,723.70
Minimum (Overall)	31,048.00	264.90
Maximum (Overall)	43,313.00	48,167.70
Mean (Overall)	37,180.08	16,179.36
Standard deviation (Overall)	3,554.16	15,075.35

Source: Own processing.

The development of import in a time perspective is obviously interesting. Therefore the Figure 1 shows selected statistical characteristics in a graphic form; including the histogram of the input data.

Figure 1: Graph of basic statistical characteristics



Source: Own processing.

The data processing will be carried out by Statistica software version 12 of DELL Inc. The linear regression will be performed first, followed by the use of neural networks for the purpose of regression.

The linear regression will be performed on the examined data sample for the following functions:

- Linear,
- Polynomial,
- Logarithmic,
- Exponential,
- Distance weighting polynomial,
- Negative exponential smoothing polynomial.

First the correlation coefficient will be calculated, i.e. the time dependence of the USA import from China. Further we will deal with the significance level at 0.95.

After that the regression will be performed with the help of neural structures. We will generate the multi-layer perceptron networks and the neural networks of basic radial function. The independent variable will be time. The dependent variable is defined as the USA import from China. The time series will be divided into three sets, i.e. training, testing and validation. The first one includes 70% of input data. The neural structures will be generated on the base of the training data set. The two remaining sets will contain 15% of remaining information. Both sets will serve as a tool for the verification of the discovered neural structure, i.e. the discovered model. The delay of the time series will be 1. We will generate 10,000 neural networks. Five of them which will have the best characteristics will be preserved1. There will be a minimum of two neurons in the hidden layer; however, the maximum will be 50. In case of radial basic function there will be at least 21 neurons and at the most 30 neurons in the hidden layer. The following distribution functions will be considered for a multiple perceptron network in both the hidden and output layers:

- Linear,
- Logistic,
- Atanh,
- Exponential,
- Sinus.

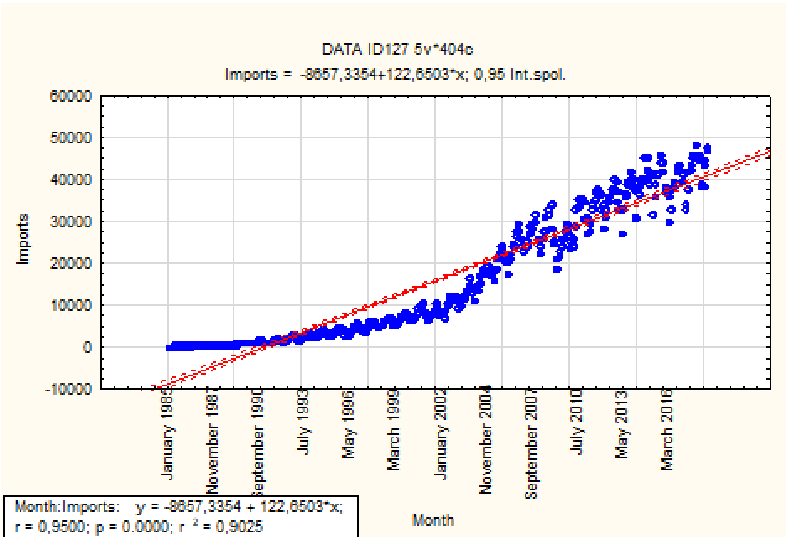
Results

Linear regression

The correlation coefficient equals to 0.95, which means a significant statistical direct dependence of the USA import from China on the time development. The coefficient of determination acquires the value of 0.9025.

A scatterplot has been formed (for more details, see Figure 2) in which the individual points were fitted with a regression curve; in this case linear. The parameters of the curve are clearly shown in the graph.

Figure 2: The scatterplot of the USA import from China with fitted regression curve – linear function



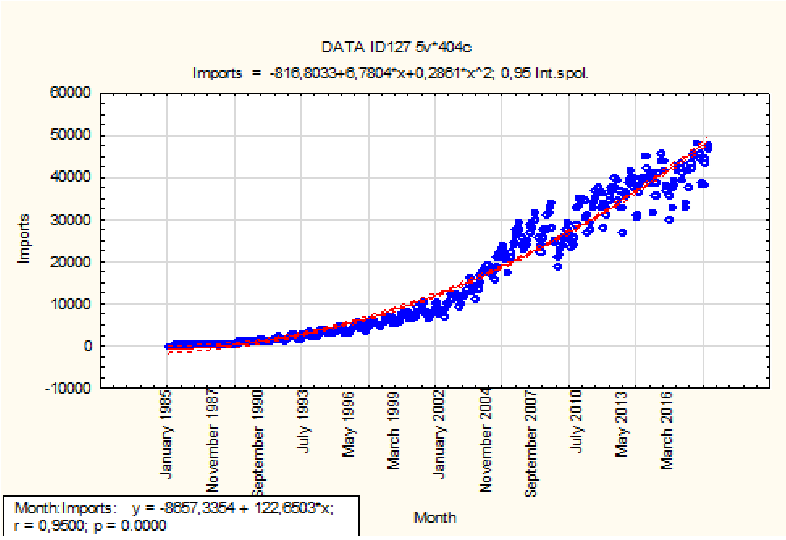
Source: Own processing.

We will use the least squares method. The generating of networks will be terminated unless there is an improvement, i.e. the reduction of the value of the aggregate of squares.

Therefore we will preserve such neural structures which will have the lowest aggregate of squares of residua in relation to the real development of the USA import from China, i.e. zero in an ideal manner.

The full line represents a regression function. The straight line does not balance the time series quite accurately. Figure 3 shows the scatterplot fitting with the polynomial function.

Figure 3: Scatterplot of the USA import from China with fitted regression curve – polynomial fiction

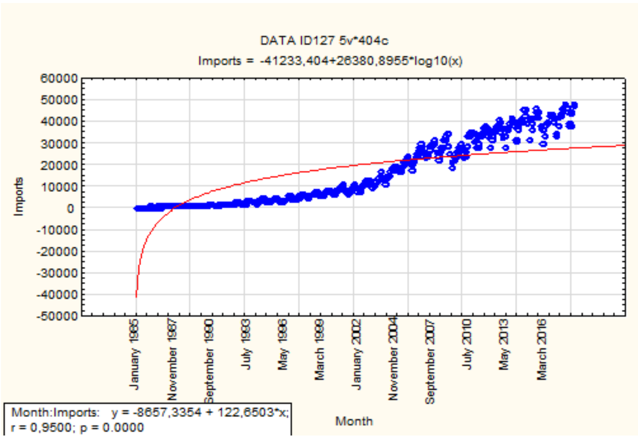


Source: Own processing.

It is immediately obvious that the polynomial function balances the time series markedly more accurately then the straight line of the linear function.

Figure 4 shows the scatterplot fitting with the logarithmic function.

Figure 4: Scatterplot of the USA import from China with fitted regression curve – logarithmic function

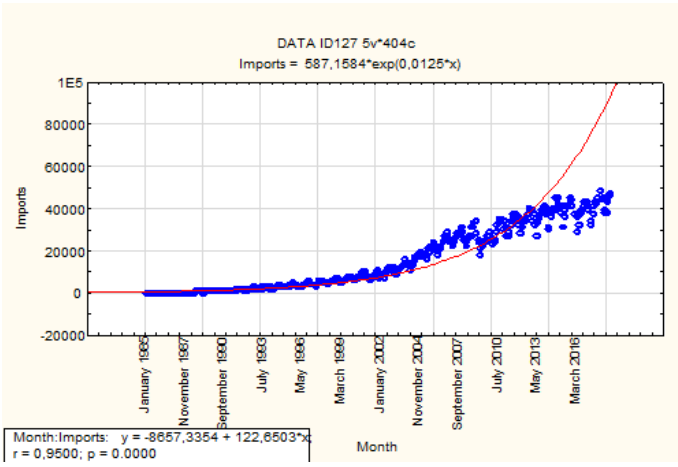


Source: Own processing.

The shape of hyperbola and the location of individual points in the graph clearly show that the logarithmic function is not suitable for a regression.

Figure 5 provides a scatterplot of the USA import from China which is interspaced with an exponential function.

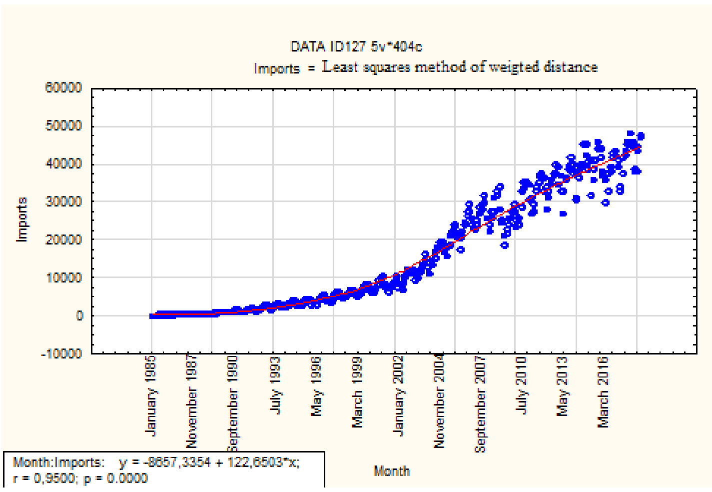
Figure 5: The scatterplot of the USA import from China interspaced with the regression curve – exponential function



Source: Own processing.

The figure clearly shows that the curve has been gaining unreal values since 2013. Even this fitting of data of the USA import from China is not appropriate. Figure 6 presents a scatterplot of the development of the USA import from China with fitted with function obtained by using the least squares method of distance weighting.

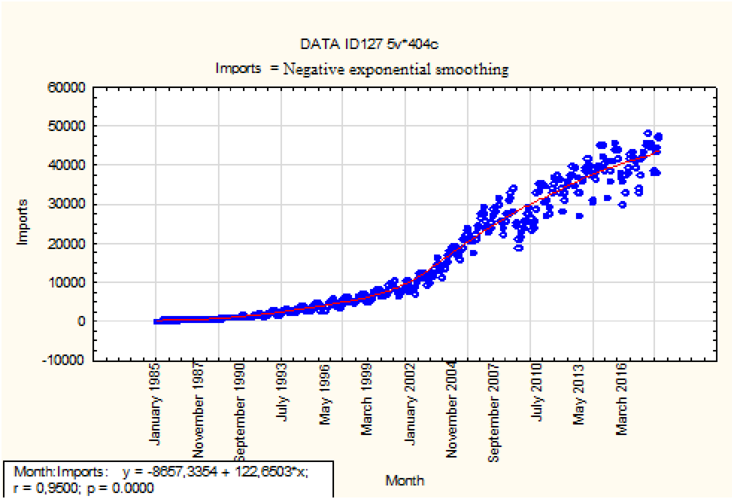
Figure 6: Scatterplot of the USA import from China with fitted regression curve – function MLS distance weighting



Source: Own processing.

The curve quite appropriately copies the development of the USA import from China in its total interval. Figure 7 presents the fitting with a function. It has been obtained with the help of the least squares method in a negative manner, i.e. exponential smoothing.

Figure 7: Scatterplot of the USA import from China with fitted regression curve – function MLS negative exponential smoothing



Source: Own processing.

Even this curve seems interesting and appropriate for an eventual prediction.

As mentioned above, the correlation coefficient at 0.95 indicates a significant statistical indirect dependence of the targeted variable on the time development. If we considered the results merely by an optical comparison of the development of the USA import from China and by a shape of regression curve and if we considered a simple linear regression at the same time, we could definitely conclude that the curves obtained by the method of least squares - negative-exponential smoothing and by the method of the least squares of weighting distances correspond with the development the most. The polynomial function would certainly hold the third imaginary position. All the three functions follow the basic development of the USA import from China.

Neural structures

There have been generated 10.000 neural networks on the base of the defined procedure. Five of them that have the best parameters have been preserved. They are presented in Table 2.

Tab. 2: The list of retained neural networks

Index	Network designation	Training perform.	Testing perform.	Valid. perform.	Training. error	Testing error	Valid. error	Training algorithm	Error function	Activation hidden layer	Output activat. function
1	RBF 1-28-1	0.985565	0.993687	0.988204	3199247	2234000	2510302	RBFT	Sum of squares	Gauss	Identity
2	RBF 1-24-1	0.981934	0.994521	0.988715	3985467	2272140	2446088	RBFT	Sum of squares	Gauss	Identity
3	RBF 1-25-1	0.974559	0.988826	0.988329	5593698	2897250	2473482	RBFT	Sum of squares	Gauss	Identity
4	RBF 1-30-1	0.988410	0.992897	0.988280	2564933	2679733	2424616	RBFT	Sum of squares	Gauss	Identity
5	RBF 1-28-1	0.979283	0.989343	0.987745	4565578	3029347	2526599	RBFT	Sum of squares	Gauss	Identity

Source: Own processing.

There are only the neural networks of basic radial function. There is one variable in the entrance layer, i.e. time. The neural networks contain from 24 to 28 neurons in the hidden layer. Consequently, there is a single neuron and a single output variable in the output layer, i.e. the USA import from China. The training RBFT algorithm was applied in case of all the networks. Moreover, all the neural structures used the same function for the activation of the hidden layers of neurons, Gauss curve in particular. Similarly, the same function is used for the activation of the external layer of neurons, i.e. the identity function (see Table 2).

The training, testing and validation performances are definitely interesting. In general, we look for such a network that has an identical performance in the same data sets, i.e. ideally. Let us remind of the fact that the distribution into the sets was coincidental. The error ought to be the smallest possible.

The performance of individual data sets is defined in the form of correlation coefficient. The values of individual data sets based on the individual neural networks are shown in Table 3.

Tab. 3: Correlation coefficients of individual data sets

Network	Imports (Training)	Imports (Testing)	Imports (Validation)
1.RBF 1-28-1	0.985565	0.993687	0.988204
2.RBF 1-24-1	0.981934	0.994521	0.988715
3.RBF 1-25-1	0.974559	0.988826	0.988329
4.RBF 1-30-1	0.988410	0.992897	0.988280
5.RBF 1-28-1	0.979283	0.989343	0.987745

Source: Own processing.

The conclusion, based on the table, is that the performance of all the neural structures is roughly identical. The insignificant differences bear no influence on the performance of individual networks. The value of the correlation coefficient of all the training sets is in the interval from more than 0.974 to 0.988. The value of the correlation coefficient of testing data sets acquires more than 0.988 in case of all the neural networks. The correlation coefficient of validation data set of all the neural networks is above the level of 0.987. We need to carry out the more detailed analysis in order to select the most appropriate neural structure. Table 4 shows the basic statistical characteristics of the individual data sets for all the neural structures.

Tab. 4: The statistics of individual data sets according to the retained neural networks

Statistics	**1.RBF 1-28-1**	**2.RBF 1-24-1**	**3.RBF 1-25-1**	**4.RBF 1-30-1**	**5.RBF 1-28-1**
Minimal prediction (Training)	-105.81	580.89	121.1	-246.8	-297.8
Maximal prediction (Training)	45.281.06	46.726.83	46.002.4	44.572.1	44.832.3
Minimal prediction (Testing)	-17.55	875.04	204.9	-236.1	-66.6
Maximal prediction (Testing)	43.523.94	43.272.06	45.755.1	41.867.8	44.650.5
Minimal prediction (Validation)	-115.73	782.33	664.4	-228.6	-361.7
Maximal prediction (Validation)	43.676.46	43.430.95	45.447.6	41.848.5	44.800.2
Minimal residua (Training)	-9.388.83	-9.090.02	-12.440.4	-11.451.6	-10.678.7
Maximal residua (Training)	9.830.06	11.453.48	13.102.8	8460.7	10.527.1
Minimal residua (Testing)	-29.29.57	-4.211.16	-4.982.3	-3.175.6	-6.051.8
Maximal residua (Testing)	85.48.44	8.099.91	9.591.5	7.255.6	9.059.8
Minimal residua (Validation)	-84.38.26	-7.010.75	-6.153.3	-8.573.7	-6.018.4
Maximal residua (Validation)	4.860.34	3.833.17	7.097.7	6.317.5	6.693.0
Minimal standard residua (Training)	-5.25	-4.55	-5.3	-7.2	-5.0
Maximal standard residua (Training)	5.50	5.74	5.5	5.3	4.9
Minimal standard residua (Testing)	-1.96	-2.79	-2.9	-1.9	-3.5
Maximal standard residua (Testing)	5.72	5.37	5.6	4.4	5.2
Minimal standard residua (Validation)	-5.33	-4.48	-3.9	-5.5	-3.8
Maximal standard residua (Validation)	3.07	2.45	4.5	4.1	4.2

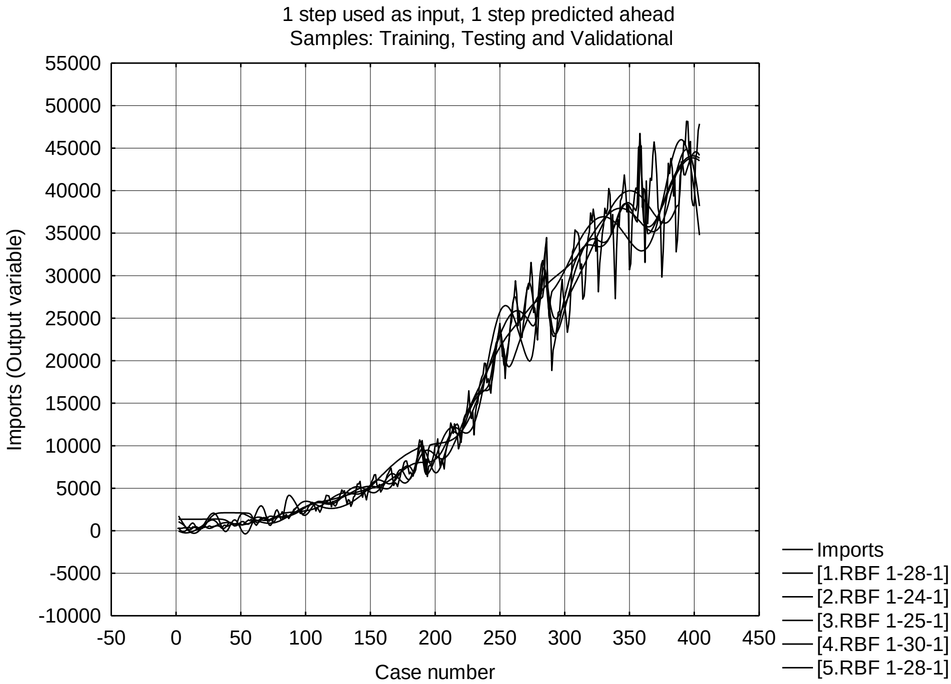
Source: Own processing.

The individual statistics of a neural network are in an overall cross-sectional consensus in all the sets, i.e. minima, maxima, residua; in an ideal case. In case of balanced time series, however, the differences are minimal. There are more significant differences in case of residua. Nevertheless, we are not able to clearly identify the neural network with the most appropriate results.

Figure 8 presents a line chart which displays a real development of the USA import from China and the development of the individual predictions with the tool of individual, generated and retained networks.

The graph clearly shows that all the neural networks predict a development of the USA import from China in the individual intervals with subtle differences. The similarity of the predictions of individual networks is not important but it is the similarity, i.e. the degree of consensus, with the real development of the USA import from China that matters. It is appropriate to claim that all the preserved neural networks seem very interesting at first sight. They respect the curve directions and tend to, although not quite accurately, take into account the extremes of the curve.

Figure 8: Line chart – the development of the USA import from China predicted by the neural networks in comparison with the real development of import in the monitored period



Source: Own processing.

Conclusion

The aim of the paper was to compare the accuracy of the equalizing time series by means of regression analysis and the neural networks on the example of the USA import from China.

In general, every prediction is determined by a degree of probability, which causes its fulfilment. When we predict a future development of any variable, we attempt to estimate the future development of the variable on the basis of the past data. Although we are able to integrate the majority of factors which influence the targeted value into the model, it is always the case of the simplification of reality and we always deal with a certain degree of probability that some predicted scenario will take place. In both cases of the linear regression and the regression with the use of neural networks there is a simplification, which is quite substantial. We deal with two quantities, i.e. the input (time) and the output (the USA import from China). Thus we utterly ignore certain input quantities which often bear a substantial significance on the USA import from China, i.e. the international political situation, taxation in both countries, price of production factors, state support for export, life standard of inhabitants in both countries, and many others). Despite this fact or because of this fact that there are a great number of factors influencing the USA import from China, it is necessary to reconsider, whether the use of time series causes an excessive simplification of the targeted variable or, on the contrary, the other variables are so insignificant that the input variable, i.e. time, and the output variable, i.e. the USA import from China, are entirely sufficient. The purpose of the calculation is thus crucial. It is valid that the aggregated variables are estimated better than the partial variables.

Concurrently we may claim that the significant simplification of reality results in the impossibility of the prediction of extraordinary events and their influence on the USA import from China. Perhaps it is possible in the short time perspective but certainly not in the long term. The ideal prediction would be in the matter of days. However, it is not currently possible to acquire data for such a short prediction.

The USA import from China can be defined on the basis of statistical, causal and intuitive methods. We have dealt with the comparison of statistical methods in this case. They have provided just a mere possible framework of the development of monitored variable. It is necessary to subsequently work with information about the future development of economic, political or legal environment. If we are able to predict its development, we can subsequently project it into the monitored variable. Concurrently the personality of evaluator, i.e. economist, comes into sight. He or she corrects the price, which is defined by the statistical methods and specified on the basis of causal links, on the basis of his or her expertise and experience.

The objective of the paper has been fulfilled.

The best curve out of linear regression, from the optical view, seems the one acquired by the least squares method – negative exponential smoothing and the curve acquired by the least squares method of weighting distances. All the preserved structures of neural networks have proved to be useful in practice. If we view the performance from the perspective of correlation coefficient, only the neural networks remain to be used and there is hardly any difference between them from the practical point of view.

References

BERNARD, A. B., 2004. Exporting and Productivity in the USA. *Oxford Review of Economic Policy*. **20**(3), 343-357. ISSN 1460-2121.

DE SOUZA, A. F., FREITAS, F. D. and DE ALMEIDA, A. G. C. 2010. High performance prediction of stock returns with VG-RAM weightless neural networks. In: IEEE. *2010 Workshop on High Performance Computational Finance at SC10 (WHPCF).* 1-8. ISBN 978-1-4244-9062-2.

DONGDONG, H. and WENHONG, Z., 2011. The Forecast of Price Index Based on Wavelet Neural Network. In: IEEE. *2011 Fourth International Conference on Business Intelligence and Financial Engineering.* 32-36. ISBN 978-1-4577-1541-9.

FALAT, L. and PANCIKOVA, L., 2015. Quantitative Modelling in Economics with Advanced Artificial Neural Networks. *Procedia Economics and Finance*. **34**, 194-201. ISSN 2212-5671.

FÜRST, R. and PLESCHOVÁ, G., 2010. Czech and Slovak Relations with China: Contenders for China's Favour. *Europe-Asia Studies*. **62**(8), 1363-1381. ISSN 0966-8136.

GENG, Y., TIAN, X., SARKIS, J. and ULGIATI, S., 2017. China-USA Trade: Indicators for Equitable and Environmentally Balanced Resource Exchange. *Ecological Economics*. **132**, 245-254. ISSN 0921-8009.

HORÁK, J. and KRULICKÝ, T., 2018. Comparison of neural networks and regression time series in estimating US and China trade balance. In: Magnanimitas. *International Masaryk Conference for Ph.D. Students and Young Researchers*. 244-253. ISBN 978-80-87952-27-6.

KOURENTZES, N., 2013. Intermittent demand forecasts with neural networks. *International Journal of Production Economics*. **143**(1), 198-206. ISSN 0925-5273.

LIU, Z., ZHENG, Z., LIU, X. and WANG, G., 2009. Modelling and Prediction of the CNY Exchange Rate Using RBF Neural Network. In: Wang, S. Y., Yu, L., Wen, F. H., He, S. Y., Fang, Y., Lai, K. K. *2009 International Conference on Business Intelligence and Financial Engineering*. 38-41. ISBN 978-0-7695-3705-4.

PAO, H., 2008. A comparison of neural network and multiple regression analysis in modelling capital structure. *Expert Systems with Applications.* **35**(3), 720-727. ISSN 0957-4174.

PESARAN, M. H. and SMITH, R. P., 2014. Signs of impact effects in time series regression models. *Economics Letters*. **122**(2), 150-153. ISSN 0165-1765.

ROWLAND, Z. and VRBKA., J., 2016. Using artificial neural networks for prediction of key indicators of a company in global world. In: Klieštik, T. *16th International Scientific Conference on Globalization and its Socio-Economic Consequences*. Rajecké Teplice, Slovakia, 1896-1903. ISBN 978-80-8154-191-9.

SAYADI, A. R., TAVASSOLI, S. M. M., MONJEZI, M. and REZAEI, M., 2012. Application of neural networks to predict net present value in mining projects. *Arabian Journal of Geosciences***.** **7**(3), 1067-1072. ISSN 1866-7538.

SÁNCHEZ, D. and MELIN, P., 2015. Modular Neural Networks for Time Series Prediction Using Type-1 Fuzzy Logic Integration. In: Melin, P., Castillo, O., Kacprzyk, J. *Studies in Computational Intelligence: Design of Intelligent Systems Based on Fuzzy Logic, Neural Networks and Nature-Inspired Optimization*. **601**, 141-145. ISBN 978-3-319-17747-2.

SLOBODA, B., 2005. Forecasting, time series, and regression: An applied approach, 4th edition. *International Journal of Forecasting*. **21**(2), 391-392. ISSN 0169-2070.

ŠULEŘ, P., 2017. Using Kohonen´s neural networks to identify the bankruptcy of enterprises: Case study based on construction companies in South Bohemian region. In: Dvouletý, O., Lukeše, M., Mísař, J. *Proceedings of the 5th International Conference Innovation Management, Entrepreneurship and Sustainability*. 985-995. ISBN 978-80-245-2216-6.

TEALAB, A., 2018. Time series forecasting using artificial neural networks methodologies: A systematic review. *Future Computing and Informatics Journal.* **3**(2), 334-340. ISSN 2314-7288.

Trading economics, *United States Imports from China* [online]. [2019-03-28]. Available at: https://tradingeconomics.com/united-states/imports-from-china

VRBKA, J. a ROWLAND, Z., 2017. Stock price development forecasting using neural networks. In: Váchal, J., Vochozka, M., Horák, J. *SHS Web of Conferences - Innovative Economic Symposium 2017: Strategic Partnership in International Trade.* **39**. ISSN 2261-2424.

ZIYADIN, S., SUIEUBAYEVA, S., KABASHEVA, N. and MOLDAZHANOV, M., 2017. Economic rationale for the investment attractiveness of China at present. *Economic Annals-XXI.* **163**(1-2), 35-40. ISSN 1728-6220.

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