Machine learning forecasting of CR import from PRC in context of mutual PRC and USA sanctions

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Abstract. Mutual trade restrictions between the USA and the PRC caused by the USA feeling of imbalance of trade between these two countries have significantly influenced not only the trade between these two states but also the overall atmosphere of the international trade in the last few years. The objective of the contribution is to find out whether machine learning forecasting is capable of equalizing time series so that the model effectively forecasts the future development of the time series even in the context of an extraordinary situation caused by such factors as the mutual sanctions of the USA and PRC. The dataset shows the course of the time series at monthly intervals starting from January 2000 to June 2019. There is regression carried out using neural structures. Three sets of artificial neural networks are generated. They are differ in the considered time series lag. 10,000 neural networks are generated, out of which 5 with the best characteristics are retained. The mutual USA and PRC sanctions did not affect the success rate of the machine learning forecasting of the CR import from the PRC. It is evident that the mutual sanctions shall affect the trade between the CR and the PRC.
Key words: machine learning, mutual sanctions, import, artificial neural networks, forecasting, time series

1 Introduction

Stehel and Šuleř [1] argue that China is for the Czech Republic the principal exporter and the second principal importer with ratio 12.4% and 10.3%; however, the Czech Republic has a substantial trade deficit with People's Republic of China. Chinese imports to the Czech Republic have substantially increased with the policy focused on the investment goods and products used for further production [2]. According to Higgins, Tha and Zhong [3] it is mostly transportation equipment and machines, industrial and market products that are the predominating negotiable groups. Liu [4] declares that both economies – the Czech and Chinese one – are focused rather on the export than import. What is typical for the

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current situation is the decrease in the import from China to the Czech Republic, thus copying the global trend when China has reduced its export recently. In contrast to the change in the import from China to the Czech Republic, there is a steady increase in export of goods and services from the Czech Republic to China [5]. The drop of import and the growth of export significantly reduced the balance from minus 421 to 387 billion. All the same it cannot be currently expected that the Czech Republic would encourage the export to China more than the import from the country in the near future. Nevertheless, a lot of complaints have been made from Czech enterprises and end-to-end consumers about variable quality of the import from China. If these Czech enterprises keep on exercising a growing influence in China, a gradual improvement of the balance sheet could be expected in the following years [6]. Ministry of Foreign Affairs [7] publishes on its websites that the deficit of the Czech Republic in trading with China rose from 75.8 billion to 90.9 billion in the first two months of 2019. While the Czech export has fallen in the year-on-year balance roughly by 4% this year, the import has increased by 17%. Different states generally tend to impose economic sanctions nowadays more than before, but rarely do they achieve intended political or economic aims. Li; Crăciun et al. [8, 9] argues that what plays the key role in assessing the effectiveness of sanctions are cultural standards of target countries. The author's study reveals that in order for the effective and prosperous sanctions to be imposed as a means of foreign policy, the initiators of the sanctions must consider their cultural consequences and responsibility. The USA imposes a wide range of sanctions against China. Although the American sanction did not radically affect the trade between the countries, their impact on producers and consumers was rather profound in both countries [10].

In order to thoroughly assess the import development, it is convenient to consider employing methods such as artificial neural networks (ANNs). Kliestik [11] argues that these networks constitute computational models which reflect biological neural networks and behaviour of neurons. These networks can be applied in various areas. According to Pao [12] artificial neural networks are currently widely used for resolving possible future issues including without limitations value prediction. Sayadi et al. [13] declares that one of the big advantages of artificial neural networks is the ability to learn, generalize etc. On the other hand, Rowland and Vrbka [14] argue that disadvantages of ANNs lie in their requirements for extremely precise information and the risk of illogical behaviour of the network. Horák and Krulický [15] point out that ANN is one of the most conventional methods which is used as a prediction method that requires a more complex model, is inclined to non-linearity and employs more variables. For that reason, ANN is most effectively used in the financial sector. The authors' study reports that ANNs as a prognostic model could considerably exceed the minimum return. Cho, Kim and Bae [16] proclaim that ANN techniques achieve better results than traditional statistical methods. Comprehensive and exact results are also yielded by modern hybrid models which combine statistical and ANN methods. Li et al. [17] emphasize that traditional statistical methods are, though, very popular for their simplistic interpretation, understanding and a fine prognostic performance. Balcaen and Ooghe [18] received a surprising result having compared selected models that resulted from the discrimination analysis with models that were based on logistic regression. They found out that the accuracy of the model crucially depends on ratios included in the model itself rather than the method from which the model was derived.

The economic sector may also use other models than already mentioned neural networks. These are for example discrimination analysis, ARIMA model, cluster analysis and decision trees [19]. According to Majerčíková and Bartošová [20] multiple discrimination analysis is a diagnostic method which consists in assessing and interpreting future economic risks. The advantage of this analysis is its low time consumption and simplicity. Kliеštik, Vrbka and Rowland [21] see its drawbacks in its non-comprehensiveness. ARIMA model (Autoregressive Integrated Moving Average) is one of the most widely used linear models applied in predicting time series [22]. The models are mostly used for a short-term prognosis in situations when information on variables is not available or when the model does not have a good prognosis [23]. Junttila [24] sees the advantages of the model mostly in its ability to readily adapt to changes throughout the time series. On the other hand, he spots disadvantages in them being applicable only for time series ranging from no less than 50 observations; furthermore, final models are hard to interpret and their practical application is very difficult. Majerová and Kliеštik [25] argues that the main purpose of the cluster analysis is to generalize and define relations in the group of variables. Their clusters are created according to their similarity. The aim of the cluster analysis is to classify an exact number of objects into several relevant homogeneous clusters. What is required is that the objects inside one cluster should be extremely similar while the objects in different clusters should be as different as possible [26]. According to Šuleř [27] this method is convenient for its simplicity; it allows using statistical software etc. The drawback of the cluster analysis is its inclination to distorting the results. Chollet [28] in his study points out that decision trees are data structures that are able to predict output values for specific inputs or to classify input data points. Their advantage is an easy visualization and interpretation. On the other hand, their disadvantage is that they cannot be always used since they require a more difficult continuous data processing [29].

Rowland, Šuleř and Vochozka [30] aimed at comparing the accuracy of equalizing the time series through ANNs and regression analysis giving the trade balance between the Czech Republic and China as an example. At first they carried out linear regression followed by regression via ANNs. Then they professionally compared both methods. According to their study ANNs appear very useful for predicting time series. Weijin and Yuhui [31] suggest a model which is used for predicting import and export trades in one sector. They concluded that a non-linear prediction may focus not only on the combination of data and improving their accuracy, but it can also vividly reflect non-linear characteristics of the prognosis system. Horák, Šuleř and Vrbka [32] focused on comparing accuracies of equalizing time series through the regression analysis and ANNs giving the export from the USA to China as an example. The aim of the study was to illustrate a possible use and advantages of ANNs in practice. The study compares two statistical methods while artificial intelligence does not apply in either of these techniques. On the other hand, a lot of economic sectors showed better results. It was found out that ANNs can effectively learn dependences of time series. As applied by analogy, Vrbka, Rowland and Šuleř [33] received the same results in their study where they compared the accuracy of the equalization of time series through regression analysis and ANNs giving the trade balance between the EU and China as an example.

2 Data and methods

Mutual trade restrictions between the USA and the PRC caused by the USA feeling of imbalance of trade between these two countries have significantly influenced not only the trade between these two states but also the overall atmosphere of the international trade in the last few years. In a way the restrictions also affect the trade between the countries that are out of this trade war. It is therefore very interesting to see how the trade war is reflected in the relations that are not related to it at first sight. This contribution is focused on the machine learning forecasting of the CR import from the PRC. Its objective is to find out whether machine learning forecasting is capable of equalizing time series so that the model effectively forecasts the future development of the time series even in the context of an extraordinary situation caused by such factors as the mutual sanctions of the USA and PRC.

The dataset shows the course of the time series at monthly intervals starting from January 2000 to June 2019. The course of the time series is shown in Figure 1.

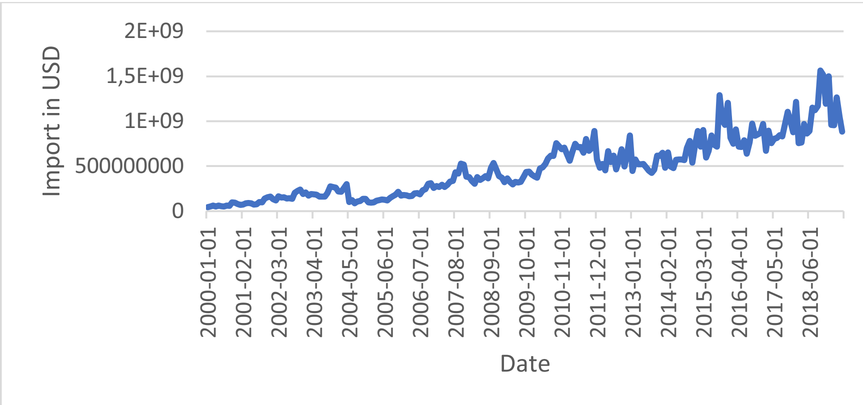

Fig. 1. Development of CR import from PRC between January 2000 to July 2019

Note: The values in the entire text are given in USD.

Source: World Bank [34], own processing.

The Figure clearly shows the overall increase of the CR import from the PRC. In the first years of the monitored period the increase was rather gradual. In May 2004, the import decreased significantly almost to the third of the previous month. It was almost as if the development was the same as back in 2004. On the contrary, the highest values were achieved in October 2018 and January 2019, when the import volume was approximately USD 1.5 bn. per month. There is also a question if it is possible to find seasonal trends in the development of the time series. We will work with the assumption when setting the methodology of work. The difference between the month with the highest volume of import achieved and the month with the smallest volume of the CR import from the PRC is more than 35 higher. Table 1 shows the basic statistical characteristics of the dataset.

Table 1. Basic statistical characteristics of examined dataset

Samples	Date (Input variable)	Month (Input variable)	Year (Input variable)	Import (Output (target))
Minimal (Training)	36556.00	1.00000	2000.000	4.421794E+07
Maximum (Training)	43646.00	12.00000	2019.000	1.513269E+09
Average (Training)	40050.47	6.45455	2009.115	4.752065E+08
Standard deviation (Training)	2001.16	3.50688	5.473	3.213289E+08
Minimal (Testing)	36585.00	1.00000	2000.000	4.983804E+07
Maximum (Testing)	43677.00	12.00000	2019.000	1.563688E+09
Average (Testing)	40130.09	6.00000	2009.371	4.666358E+08
Standard deviation (Testing)	2418.96	3.38683	6.691	3.892610E+08
Minimal (Validation)	36646.00	1.00000	2000.000	5.050822E+07
Maximum (Validation)	43373.00	12.00000	2018.000	1.204702E+09
Average (Validation)	40412.86	6.71429	2010.086	5.065008E+08
Standard deviation (Validation)	3403.28	3.44159	9.284	4.082950E+08
Minimal (Overall)	36556.00	1.00000	2000.000	4.421794E+07
Maximum (Overall)	43677.00	12.00000	2019.000	1.563688E+09
Average (Overall)	40116.30	6.42553	2009.298	4.786420E+08
Standard deviation (Overall)	2069.19	3.45140	5.669	3.305002E+08

Source: Authors.

There will be regression carried out using neural structures. We will generate multilayer perceptron networks (MLP). Three sets of artificial neural networks will be generated. They will differ in the considered time series lag:

1. 1-month lag,
2. 5-month lag,
3. 10-month lag.

Time series lag indicates the number of data used for the calculation of the following value (that is, based on the value of one previous month in the first case, five previous months in the second case, and ten previous months in the third case). Larger time series lag can result in averaging values. A small lag can result in extreme fluctuations in an equalized time series. Each time series lag entails greater demands on the complexity of the artificial neural structure, specifically the number of the neurons in the input layer will be increased. The calculation is then more demanding in terms of the IT equipment. In other settings, the experiments will match.

The independent continuous variable will be time. The seasonal fluctuation will be represented by categorical variable in the form of the month and the year in which the value was measured. We will thus work with the monthly seasonality of the time series. The variable in the form of the year will help to capture the development of the time series. The dependent continuous variable will be the CR import from the PRC.

The time series will be divided into three sets – training, testing and validation. The first group will contain 70% of the input data. Based on the training data set, neural structures will be generated. The remaining two datasets will contain 15% of the input information each. Both testing and validation data sets will serve to verify the reliability of the neural structure, or the model created. 10,000 neural networks will be generated, out of which 5 with the best characteristics[2]will be retained. The hidden layer will contain at least two neurons and at most 8 neurons for Experiment 1 and 9 neurons for Experiments 2 and 3. For the distribution functions in the hidden and output layers, the following functions will be considered: Linear, Logistic, Atanh, Exponential, Sinus.

Other settings will remain default (according to the ANN – automated neural networks tool). It is also possible to manually adjust the weights of the neural networks using the VNN (own neural networks). However, if there is a more appropriate weights distribution, it will most likely be a coincidence.

Finally, there will be a comparison of the three experiments carried out and it will be determined if the chosen methodology of machine learning forecasting is correct in terms of the direction and what time lag is the closest to the correct result.

3 Results

3.1 Experiment 1 (1-month lag of the time series)

Table 2 shows an overview of the neural networks retained from the Experiment 1.

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[2] The least squares method will be used. Generating of networks will be terminated if there is no improvement, i. e. the reduction in the value of the sum of the squares. We will thus retain the neural structures whose sum of the residual squares to the actual CR import from the PRC is as low as possible (zero in ideal case).

Table 2. Retained neural networks from Experiment 1

Network	Train. perform	Test. Perform.	Valid perform.	Train. error	Test. error	Valid. error	Train. Algorit.	Error function	Activation of hidden layer	Output activation function
MLP 3-10-1	0.963883	0.966223	0.947668	3.596561E +15	4.769768E +15	6.024952E +15	BFGS (Quasi-Newton) 139	Sum of squares	Tanh	Exponential
MLP 3-8-1	0.957052	0.963829	0.950740	4.274898E +15	5.077201E +15	5.136616E +15	BFGS (Quasi-Newton) 101	Sum of squares	Tanh	Tanh
MLP 3-9-1	0.947655	0.966741	0.947826	5.170708E +15	5.067522E +15	5.938017E +15	BFGS (Quasi-Newton) 210	Sum of squares	Exponential	Tanh
MLP 3-9-1	0.942154	0.958476	0.948380	5.739409E +15	5.941721E +15	6.174524E +15	BFGS (Quasi-Newton) 157	Sum of squares	Exponential	Logistic
MLP 3-9-1	0.944905	0.960153	0.947592	5.481413E +15	5.579881E +15	6.427599E +15	BFGS (Quasi-Newton) 47	Sum of squares	Tanh	Logistic

Source: Authors.

It results from the table that there have been retained neural networks with 8, 9, and 10 neurons in the hidden layer of the neural network. For the activation of the hidden layer, the function of the hyperbolic tangent and exponential function are used. The output layer of the neurons is activated using the exponential, logistic, and hyperbolic tangent functions. What is important is the performance of the neural networks, expressed by the correlation coefficient. The value of the correlation coefficient is high in all data sets of all networks. It achieves the values higher than 0.94 (in the case of the first network, it is above 0.96 in two data sets), which indicates a high degree of direct dependence. Based on this parameter it is evident that the retained neural structures are a plausible model of the actual time series, and are thus able to forecast the future development of the time series. However, the level of error in all three data sets is relatively high. Figure 2 represents the comparison of the actual course of the time series and equalized time series.

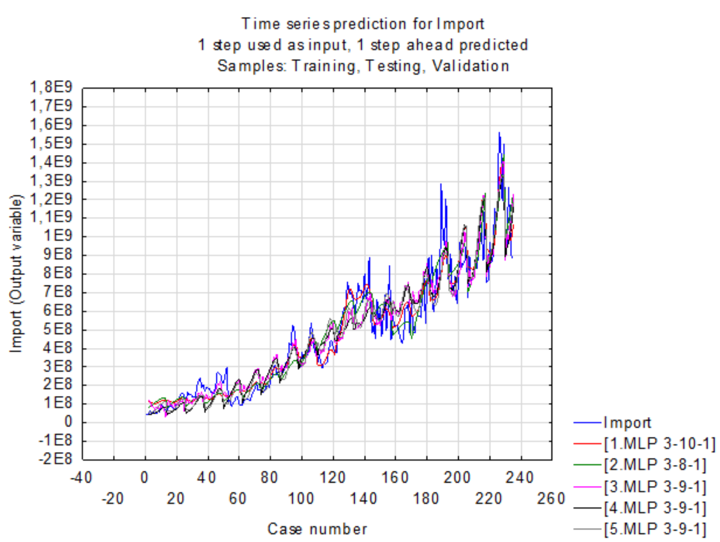

Fig. 2. Equalized time series of retained networks – Experiment 1

Source: Author.

Figure 2 shows that all equalized time series are able to follow the course of the actual development of the CR import from the PRC quite well. There have been identified deficiencies in the 40th case, 150th and 190th case, but not significant ones. In order to be able to determine the applicability of the networks, it is necessary to focus on their ability to forecast the future development. We will focus on estimating the CR development from the PRC for the period July 2019-December 2020, that is, for the period of 18 months. The concrete results are shown in Table 3.

Table 3. Development of forecasts for period of August 2019-January 2020 by networks retained from Experiment 1

Date	MLP 3-10-1	MLP 3-8-1	MLP 3-9-1	MLP 3-9-1	MLP 3-9-1
31 July 2019	1.065574E+09	1.231325E+09	1.231142E+09	1.157255E+09	1.182213E+09
31 August 2019	1.181902E+09	1.292336E+09	1.294608E+09	1.228682E+09	1.248790E+09
30 September 2019	1.372477E+09	1.415371E+09	-1.424833E+09	4.432479E+07	1.348762E+09
31 October 2019	1.569194E+09	1.488292E+09	-1.424833E+09	4.421795E+07	1.412637E+09
30 November 2019	1.730247E+09	1.510818E+09	-1.424833E+09	4.421794E+07	1.448757E+09
31 December 2019	1.824783E+09	1.513196E+09	-1.424833E+09	4.421794E+07	1.466828E+09
31 January 2020	1.854371E+09	1.513268E+09	-1.424833E+09	4.421794E+07	1.475707E+09
29 February 2020	1.287440E+09	1.420006E+09	-1.424833E+09	4.421794E+07	1.375046E+09
31 March 2020	1.228724E+09	1.470567E+09	-1.424833E+09	4.421794E+07	1.410437E+09
30 April 2020	1.189816E+09	1.502848E+09	-1.424833E+09	4.421794E+07	1.436289E+09
31 May 2020	1.212808E+09	1.512284E+09	-1.424833E+09	4.421794E+07	1.454421E+09
30 June 2020	1.330846E+09	1.513244E+09	-1.424833E+09	4.421794E+07	1.468460E+09
31 July 2020	1.556136E+09	1.513268E+09	-1.424833E+09	4.421794E+07	1.479600E+09
31 August 2020	1.875536E+09	1.513269E+09	-1.424833E+09	4.421794E+07	1.488921E+09
30 September 2020	2.230543E+09	1.513269E+09	-1.424833E+09	4.421794E+07	1.496195E+09
31 October 2020	2.537059E+09	1.513269E+09	-1.424833E+09	4.421794E+07	1.501247E+09
30 November 2020	2.738303E+09	1.513269E+09	-1.424833E+09	4.421794E+07	1.504351E+09
31 December 2020	2.813416E+09	1.513269E+09	-1.424833E+09	4.421794E+07	1.505892E+09

Source: Authors.

It is evident that the 3. MLP 3-9-1 network´s forecast of the future development of the monitored variable is nonsensical. The results are negative. However, we obtained an axially symmetrical cure of the possible development of the CR import from the PRC. Other basically nonsensical results are provided by the network 4. MLP 3-9-1. The initial real values pass to the import zone which is by two orders lower. The forecast of the first retained neural network 1.MLP 3-10-1 also appears to be unrealistic. First, it shows an interesting development, but from August 2020, it starts to develop not in accordance with the previous values, as there is an extreme month-on-month increase in the CR import from the PRC. For selecting the most successful neural network, Figure 3 (development of time series and forecast) will be used.

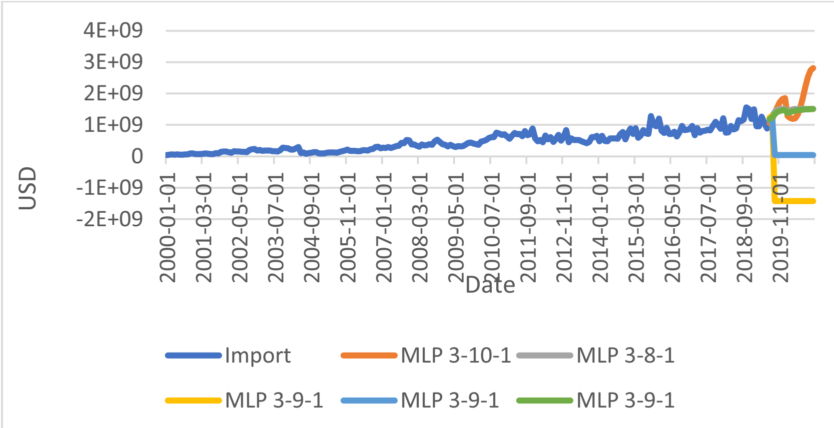

Fig. 3. Development of time series and forecasts by networks retained at Experiment 1

Source: Authors.

Due to possible distortion, there were omitted the neural networks where unrealistic forecasts of the future development of the CR import from the PRC were identified. The Figure thus captures the actual development of the time series along with the development forecast by 2.MLP 3-8-1 and 5.MLP 3-9-1. Both networks present a similar development of the time series, which ends in the monitored period, that is, in December 2020, using the similar value of the variable. For an overall comparison of the results of the partial experiments, the network 2.MLP 3-8-1 will be considered.

3.2 Experiment 2 (5-month lag of time series)

Table 4 shows the overview of the retained neural networks from Experiment 2, where a 5-month lag is assumed.

Table 4. Retained neural networks from Experiment 2

Network	Train. perform.	Test. perform.	Valid. perform.	Train. error	Test. error	Valid. error	Train. algorit.	Error function	Activation of hidden layer	Output activation function
MLP 15-5-1	0.944810	0.931109	0.940005	5.380788E+15	8.664971E+15	6.583494E+15	BFGS (Quasi-Newton) 59	Sum of squares	Tanh	Tanh
MLP 15-7-1	0.950087	0.941681	0.941613	4.880342E+15	7.504740E+15	6.307628E+15	BFGS (Quasi-Newton) 59	Sum of squares	Tanh	Identity
MLP 15-3-1	0.951657	0.951374	0.941369	4.734524E+15	6.118437E+15	6.399299E+15	BFGS (Quasi-Newton) 86	Sum of squares	Tanh	Exponential
MLP 15-4-1	0.948516	0.949282	0.940584	5.025787E+15	6.288411E+15	5.796231E+15	BFGS (Quasi-Newton) 73	Sum of squares	Logistic	Identity
MLP 15-10-1	0.970359	0.953558	0.942601	2.920810E+15	5.761694E+15	5.662860E+15	BFGS (Quasi-Newton) 182	Sum of squares	Tanh	Exponential

Source: Authors.

Due to the time series lag, the input layer contains 15 neurons. The table shows that the retained neural networks contain from 4 to 10 neurons in the hidden layer. The neural networks use the function of hyperbolic tangent and logistic function for the activation of the hidden layer. The output layer is activated using the function of hyperbolic tangent, exponential function and identity. The correlation coefficient in all data sets of all networks is very high, from more than 0.93 to more than 0.97. This indicates a high level of direct dependence. The retained neural networks shall thus be able to predict the future development of the CR import from the PRC thus precisely. The level of the error was determined by means of the sum of the least squares. The error is approximately the same as the error calculated in the first experiment. It is relatively high but regarding the high values of the variable it is still acceptable (for all networks and all data sets).

Figure 4 shows the comparison of the actual course of the time series and equalized time series.

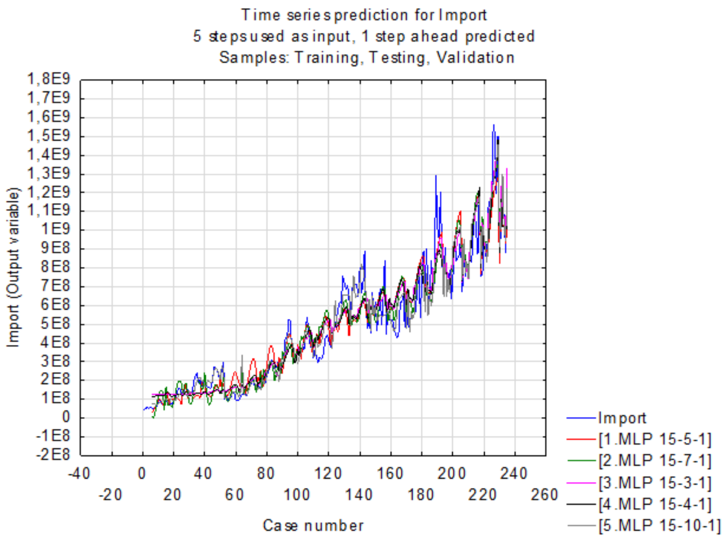

Fig. 4. Equalized time series of retained networks from Experiment 2

Source: Authors.

When comparing with Figure 2 (Experiment 1), better results are evident. The neural networks retained from the Experiment 2 are more accurate in equalizing time series. The only significant deviation is around the 190th case, where there is a sharp increase, a slight decline, repeated increase in the import volume, and then a significant decrease in the CR import (between September 2015 and December 2015. The values level off in January 2016).

In order to determine whether the networks are applicable, we will focus on their use for forecasting. We will forecast the development of the CR import from the PRC for the period of July 2019-December 2020. Table 5 shows specific data.

Table 5. Development of forecasts for the period of August 2019-January 2020 by the networks retained at Experiment 2

Date	MLP 15-5-1	MLP 15-7-1	MLP 15-3-1	MLP 15-4-1	MLP 15-10-1
31 July 2019	1.028362E+09	1.123861E+09	1.329162E+09	1.092625E+09	1.221804E+09
31 August 2019	1.118063E+09	1.202537E+09	1.326695E+09	1.227136E+09	1.340655E+09
30 September 2019	1.196789E+09	1.301656E+09	2.406627E+09	1.357579E+09	1.449726E+09
31 October 2019	1.261490E+09	1.415406E+09	1.466920E+09	1.463281E+09	1.621533E+09
30 November 2019	1.312878E+09	1.524919E+09	1.239474E+08	1.568247E+09	1.929219E+09
31 December 2019	1.351882E+09	1.611339E+09	1.239474E+08	1.761729E+09	2.516401E+09
31 January 2020	1.380977E+09	1.659723E+09	1.239474E+08	2.089505E+09	3.692948E+09
29 February 2020	1.000428E+09	1.330634E+09	1.239474E+08	1.189211E+09	1.070819E+09
31 March 2020	1.332371E+09	1.577977E+09	1.239474E+08	1.731316E+09	1.178964E+09
30 April 2020	1.263561E+09	1.470854E+09	1.239474E+08	1.641207E+09	8.136747E+09
31 May 2020	1.300011E+09	1.500345E+09	1.239474E+08	1.752477E+09	1.246006E+09
30 June 2020	1.195967E+09	1.523270E+09	1.239474E+08	1.709404E+09	5.236437E+09
31 July 2020	1.289576E+09	1.626052E+09	1.239474E+08	2.023368E+09	8.511753E+09
31 August 2020	1.357345E+09	1.737773E+09	1.239474E+08	2.277100E+09	1.187036E+10
30 September 2020	1.403060E+09	1.861599E+09	1.239474E+08	2.459162E+09	1.497943E+10
31 October 2020	1.432786E+09	1.995227E+09	1.239474E+08	2.647926E+09	1.737552E+10
30 November 2020	1.451778E+09	2.127699E+09	1.239474E+08	2.882422E+09	1.899166E+10
31 December 2020	1.463856E+09	2.241309E+09	1.239474E+08	3.123546E+09	1.999224E+10

Source: Authors.

The results listed in the table represent a possible development of the time series. At first glance we could see that it will be necessary to omit the forecasts of the 3. MLP 15-3-1 network, which achieve very low values during the monitored period, and the 5. MLP 15-10-1 network, which achieve extremely high values. The detailed course of the predictions is shown in Figure 5.

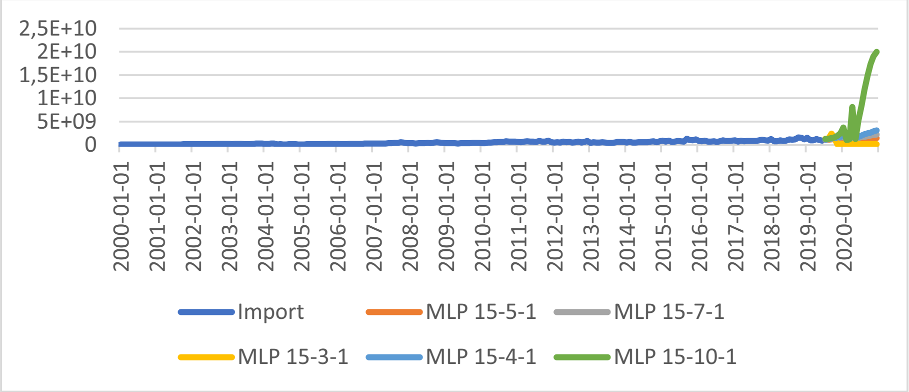

Fig. 5. Development of time series and forecasts by networks retained from Experiment 2

Source: Authors.

Comparing the actual development of the CR import from the PRC and the forecast development of the variable over time forecast using the artificial neural networks retained at Experiment 2, it can be concluded (especially considering the statistics given in Annex 2) that the 1. MLP 15-5-1 network is the best rated artificial neural structure with a potential to predict the further development of the CR import from the PRC. It is also able to capture the seasonal fluctuations as well as the overall trend of the time series.

3.3 Experiment 3 (10-month lag of time series)

For Experiment 3, 10000 artificial neural networks were generated, out of which 5 with the best characteristics were retained. For further details, see Table 6.

Table 6. Retained neural networks from Experiment 3

Network	Train. perform.	Test. perform.	Valid. perform.	Train. error	Test. error	Valid. error	Train. algorit.	Error function	Activation of hidden layer	Output activation function
MLP 30-6-1	0.939665	0.946490	0.947035	5.447619E +15	6.944809E +15	5.530532E +15	BFGS (Quasi-Newton) 67	Sum of squares	Identity	Logistic
MLP 30-3-1	0.938466	0.946155	0.949107	5.538963E +15	6.894571E +15	5.356557E +15	BFGS (Quasi-Newton) 43	Sum of squares	Identity	Logistic
MLP 30-5-1	0.920542	0.933353	0.947078	7.205668E +15	8.467160E +15	4.892436E +15	BFGS (Quasi-Newton) 11	Sum of squares	Tanh	Logistic
MLP 30-9-1	0.938393	0.946123	0.952634	5.537254E +15	6.820576E +15	4.652061E +15	BFGS (Quasi-Newton) 83	Sum of squares	Identity	Logistic
MLP 30-7-1	0.922534	0.936408	0.948838	6.936388E +15	7.931314E +15	4.862199E +15	BFGS (Quasi-Newton) 13	Sum of squares	Tanh	Logistic

Source: Authors.

The input variable and time series lag are represented by 30 neurons in the input layer. It results from the table that the neural networks with 3 – 9 neurons in the hidden layer were retained. For the activation of the hidden layer, the neural networks use the identity function and the function of hyperbolic tangent. The output layer of neurons is activated using the logistic function. The correlation coefficient of all networks is from more than 0.92 to almost 0.95, which indicates the high level of direct dependence. It appears that the retained neural structures are a very plausible model of the actual time series and are able to accurately forecast the further development of the time series. Even in this case, the method of the least squares was used for the calculation of error. Its value corresponds to the values from the previous experiments. Figure 6 shows the comparison of the actual course of the time series and equalized time series.

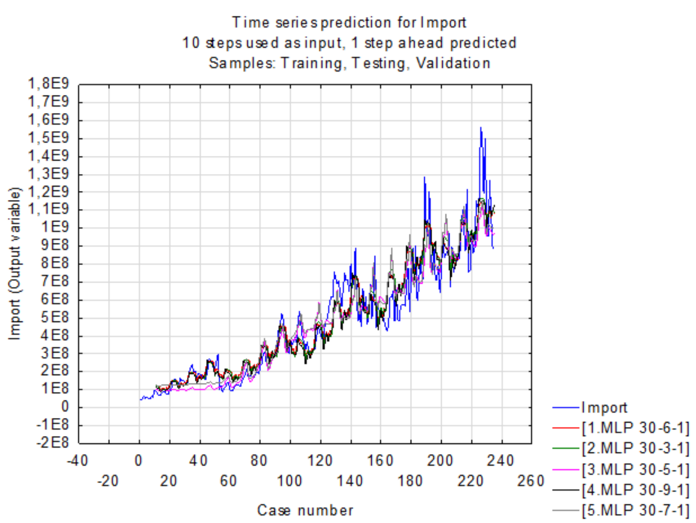

Fig. 6. Equalized time series of retained neural networks from Experiment 3

Source: Authors.

From Figure 6 it is evident that all equalized time series are able to copy the actual development of the CR import from the PRC. The course of all equalized time series is very similar. There can be some deficiencies identified around the 190th case and 225th case, where the equalized time series were not able to react adequately to extreme fluctuations

In the case of 10-month lag, we will also deal with forecasting the future development of the variable monitored. There will be forecast the development of the CR import from the PRC for the period of July 2019-December 2020. Concrete data are given in Table 6.

Table 6. Development of forecasts for the period of August 2019-January 2020 by the networks retained at Experiment 3

Date	MLP 30-6-1	MLP 30-3-1	MLP 30-5-1	MLP 30-9-1	MLP 30-7-1
31 July 2019	1.084830E+09	1.086903E+09	9.676657E+08	1.126727E+09	1.004472E+09
31 August 2019	1.169410E+09	1.148619E+09	1.024224E+09	1.150604E+09	1.067836E+09
30 September 2019	4.421794E+07	4.421794E+07	1.091852E+09	4.421794E+07	1.133239E+09
31 October 2019	4.421794E+07	4.421794E+07	1.107948E+09	4.421794E+07	1.129745E+09
30 November 2019	4.421794E+07	4.421794E+07	1.150242E+09	4.421794E+07	1.180174E+09
31 December 2019	4.421794E+07	4.421794E+07	1.116857E+09	4.421794E+07	1.149804E+09
31 January 2020	4.421794E+07	4.421794E+07	1.058804E+09	4.421794E+07	1.100857E+09
29 February 2020	4.421794E+07	4.421794E+07	1.051114E+09	4.421794E+07	1.077613E+09
31 March 2020	4.421794E+07	4.421794E+07	1.093519E+09	4.421794E+07	1.124890E+09
30 April 2020	4.421794E+07	4.421794E+07	1.101035E+09	4.421794E+07	1.129029E+09
31 May 2020	4.421794E+07	4.421794E+07	1.101716E+09	4.421794E+07	1.134081E+09
30 June 2020	4.421794E+07	4.421794E+07	1.106164E+09	4.421794E+07	1.146630E+09
31 July 2020	4.421794E+07	4.421794E+07	1.118359E+09	4.421794E+07	1.159389E+09
31 August 2020	4.421794E+07	4.421794E+07	1.146699E+09	4.421794E+07	1.190990E+09
30 September 2020	4.421794E+07	4.421794E+07	1.169352E+09	4.421794E+07	1.214999E+09
31 October 2020	4.421794E+07	4.421794E+07	1.175210E+09	4.421794E+07	1.216847E+09
30 November 2020	4.421794E+07	4.421794E+07	1.184311E+09	4.421794E+07	1.229361E+09
31 December 2020	4.421794E+07	4.421794E+07	1.179678E+09	4.421794E+07	1.226067E+09

Source: Authors.

It results from the table that the networks 1. MLP 30-6-1, 2. MLP 30-3-1 and 4. MLP 30-9-1 forecast very low values. For this reason, they will not be considered in further attempts to identify the applicability of the neural networks for forecasting. This is to certain extent confirmed by the graph in Figure 7.

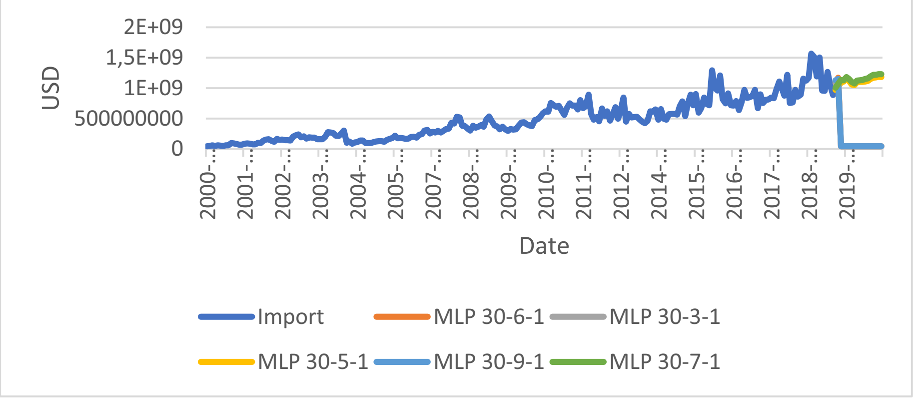

Fig. 7. Development of time series and predictions by networks retained at Experiment 3

Source: Authors.

Comparing the actual development of the CR import from the PRC and the expected development of the variable over time forecast by artificial neural networks retained at Experiment 3, it can be concluded that (especially considering the table of statistics in Annex 2) the network 5. MLP 30-7-1 shows the best predictions. However, it shall be added that the network 3. MLP 30-5-1 also shows very good characteristics.

4 Discussion

Within the research, three experiments were carried out, where the development of the time series represented by the CR import from the PRC was examined. Firstly, it was observed how the multilayer perceptron neural networks are able to equalize time series. Based on the research, other types of artificial networks were ignored, as it is considered to be proved that MLP show significantly better results in this type of tasks than other applicable neural networks. (Moreover, it is assumed that it is not suitable to use deep learning neural networks for this type of tasks). In each experiment, a total of 10,000 artificial neural networks were generated, out of which five best structures were retained. From the results described above it is evident that some of the retained neural structures were affected by overfitting. They were able to equalize the time series very well; however, their predictions do not correspond to the achieved characteristics. Other neural networks are applicable for forecasting the future development of the CR import from the PRC. The performance of the networks was always high, and the level of the error was acceptable. From each experiment, the most successful network was identified (although in two experiments, the difference between the most successful and the second most successful network was negligible). This network was subjected to further comparison (for more details, see Table 7).

Table 7. Comparison of the most successful neural structures from all experiments

Date	Experiment 1	Experiment 2	Experiment 3
	2. MLP 3-8-1	1. MLP 15-5-1	5. MLP 30-7-1
31 July 2019	1.231325E+09	1.028362E+09	1.004472E+09
31 August 2019	1.292336E+09	1.118063E+09	1.067836E+09
30 September 2019	1.415371E+09	1.196789E+09	1.133239E+09
31 October2019	1.488292E+09	1.261490E+09	1.129745E+09
30 November 2019	1.510818E+09	1.312878E+09	1.180174E+09
31 December 2019	1.513196E+09	1.351882E+09	1.149804E+09
31 January 2020	1.513268E+09	1.380977E+09	1.100857E+09
29 February 2020	1.420006E+09	1.000428E+09	1.077613E+09
31 March 2020	1.470567E+09	1.332371E+09	1.124890E+09
30 April 2020	1.502848E+09	1.263561E+09	1.129029E+09
31 May 2020	1.512284E+09	1.300011E+09	1.134081E+09
30 June 2020	1.513244E+09	1.195967E+09	1.146630E+09
31July 2020	1.513268E+09	1.289576E+09	1.159389E+09
31 August2020	1.513269E+09	1.357345E+09	1.190990E+09
30 September 2020	1.513269E+09	1.403060E+09	1.214999E+09
31 October 2020	1.513269E+09	1.432786E+09	1.216847E+09
30 November 2020	1.513269E+09	1.451778E+09	1.229361E+09
31 December 2020	1.513269E+09	1.463856E+09	1.226067E+09

Source: Authors.

Table 7 shows significant differences between the neural networks. This is even better illustrated by Figure 8.

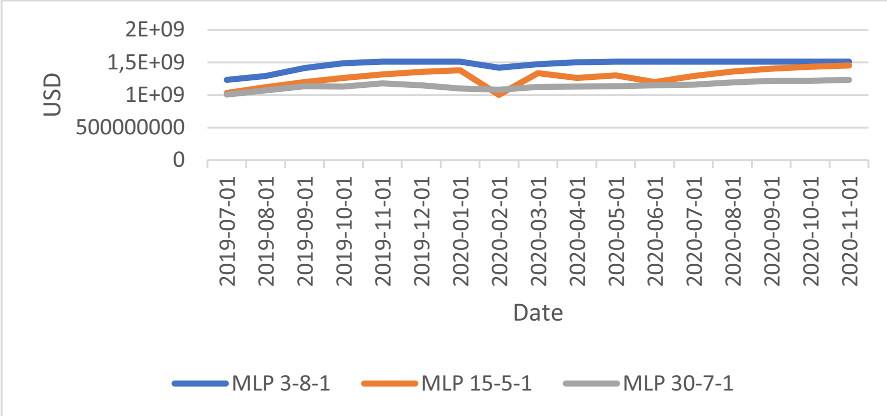

Fig. 8. Comparison of most successful neural networks from all experiments

Source: Authors.

The figure shows very similar courses of all selected neural structures. The retained network from the first experiment (with a 1-month lag of time series) shows the values calculated and derived from the fluctuation of the time series around the case No. 225. However, this is not optimal. The network from the second experiment assumes a positive development of the time series. It assumes seasonal fluctuations (the most significant one in March 2020), and accepts the overall increase in the CR import from China. The network retained in the third experiment (with a 10-month lag) equalizes the time series more than it is required. It could therefore be concluded that the best forecasting tool is the best network from the second experiment, 1. MLP 15-5-1, which is able to capture most precisely the development of the time series (with the exception of the case 190), and is able to forecast the development with its seasonal fluctuations.

5 Conclusion

The objective of the contribution was machine learning forecasting of the Czech Republic (CR) import from the People´s Republic of China (PRC).

The conclusion of the contribution can be as follows:

1. Multilayer perceptron networks are a suitable tool for forecasting the CR import from the PRC (which was proved both by research and experiments).
2. MLP networks are able to capture the trend of the whole time series as well as the seasonal fluctuations. Nevertheless, it is necessary to determine the right time series lag (that is, the time interval of the data used for the calculation of the forecast data).
3. It results from above that it is necessary to use a five-month lag.

The mutual USA and PRC sanctions did not affect the success rate of the machine learning forecasting of the CR import from the PRC. However, the question is whether the mutual USA and PRC sanctions affect significantly the trade between the CR and the PRC. In general, the PRC could be expected to look for new markets for its goods, which is mostly exposed to a duty. In such a case, the Czech Republic would also be considered. It is evident that the mutual sanctions shall affect the trade between the CR and the PRC. Nevertheless, the sanctions did not significantly influence the successfulness of the machine learning forecasting of the monitored variable development. The generated and retained neural networks (especially 1. MLP 15-5-1) have been very successful.

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Annex 1
Basic statistics of equalized time series – 1-month lag

Statistics	1.MLP 3-10-1	2.MLP 3-8-1	3.MLP 3-9-1	4.MLP 3-9-1	5.MLP 3-9-1
Minimal predictions (Training)	1.019626E+08	8.243890E+07	2.664638E+07	4.594127E+07	5.604704E+07
Maximal predictions (Training)	1.397260E+09	1.445876E+09	1.407840E+09	1.329468E+09	1.333489E+09
Minimal predictions (Testing)	1.031296E+08	7.868087E+07	8.458917E+07	4.494537E+07	5.645213E+07
Maximal predictions (Testing)	1.289120E+09	1.218565E+09	1.284406E+09	1.236164E+09	1.264197E+09
Minimal predictions (Validation)	1.058761E+08	9.279675E+07	8.606640E+07	4.742774E+07	5.687259E+07
Maximal predictions (Validation)	1.218385E+09	1.140678E+09	1.224814E+09	1.199455E+09	1.210029E+09
Minimal residuals (Training)	-2.212713E+08	-2.934693E+08	-2.625207E+08	-2.799729E+08	-2.703439E+08
Maximal residuals (Training)	4.849909E+08	3.854199E+08	4.829077E+08	4.761820E+08	4.753483E+08
Minimal residuals (Testing)	-1.861218E+08	-1.972519E+08	-1.383202E+08	-1.762328E+08	-1.943952E+08
Maximal residuals (Testing)	2.767607E+08	3.451225E+08	2.908815E+08	3.275236E+08	2.994905E+08
Minimal residuals (Validation)	-3.425319E+08	-2.648245E+08	-3.489605E+08	-3.236024E+08	-3.341759E+08
Maximal residuals (Validation)	3.042138E+08	2.507207E+08	2.246107E+08	2.583186E+08	2.893341E+08
Minimal standard residuals (Training)	-3.689617E+00	-4.488485E+00	-3.650804E+00	-3.695578E+00	-3.651492E+00
Maximal standard residuals (Training)	8.087046E+00	5.894829E+00	6.715667E+00	6.285494E+00	6.420454E+00
Minimal standard residuals (Testing)	-2.694937E+00	-2.768274E+00	-1.943066E+00	-2.286286E+00	-2.602394E+00
Maximal standard residuals (Testing)	4.007337E+00	4.843521E+00	4.086187E+00	4.248997E+00	4.009319E+00
Minimal standard residuals (Validation)	-4.412902E+00	-3.695045E+00	-4.528513E+00	-4.118224E+00	-4.168222E+00
Maximal standard residuals (Validation)	3.919242E+00	3.498256E+00	2.914806E+00	3.287410E+00	3.608904E+00

Annex 2
Basic statistics of equalized time series – 5-month lag

Statistics	1.MLP 15-5-1	2.MLP 15-7-1	3.MLP 15-3-1	4.MLP 15-4-1	5.MLP 15-10-1
Minimal predictions (Training)	2.870538E+07	2.084195E+06	1.249895E+08	1.134611E+08	7.142744E+07
Maximal predictions (Training)	1.279052E+09	1.354799E+09	1.386515E+09	1.482664E+09	1.459338E+09
Minimal predictions (Testing)	9.253505E+07	9.400378E+07	1.278659E+08	1.229188E+08	1.065232E+08
Maximal predictions (Testing)	1.179155E+09	1.251712E+09	1.249326E+09	1.252984E+09	1.302836E+09
Minimal predictions (Validation)	1.019749E+08	6.793485E+07	1.272657E+08	1.183130E+08	9.380888E+07
Maximal predictions (Validation)	1.181279E+09	1.201416E+09	1.259741E+09	1.181576E+09	1.198775E+09
Minimal residuals (Training)	-3.033300E+08	-2.885160E+08	-2.702194E+08	-2.716622E+08	-2.305341E+08
Maximal residuals (Training)	4.443217E+08	4.862127E+08	4.117377E+08	4.551818E+08	4.482359E+08
Minimal residuals (Testing)	-2.821787E+08	-3.106774E+08	-2.805951E+08	-2.616854E+08	-2.627082E+08
Maximal residua (Testing)	3.845328E+08	3.119759E+08	3.143621E+08	3.107034E+08	3.160098E+08
Minimal residuals (Validation)	-3.054264E+08	-3.255626E+08	-2.925264E+08	-2.696388E+08	-2.710663E+08
Maximal residuals (Validation)	2.292086E+08	2.769787E+08	2.457431E+08	3.414572E+08	3.138268E+08
Minimal standard residuals (Training)	-4.135161E+00	-4.129949E+00	-3.927158E+00	-3.832015E+00	-4.265633E+00
Maximal standard residuals (Training)	6.057237E+00	6.959870E+00	5.983875E+00	6.420707E+00	8.293826E+00
Minimal standard residuals (Testing)	-3.031382E+00	-3.586261E+00	-3.587235E+00	-3.299963E+00	-3.460976E+00
Maximal standard residuals (Testing)	4.130949E+00	3.601250E+00	4.018926E+00	3.918101E+00	4.163183E+00
Minimal standard residuals (Validation)	-3.764249E+00	-4.099222E+00	-3.656780E+00	-3.541682E+00	-3.602115E+00
Maximal standard residuals (Validation)	2.824898E+00	3.487492E+00	3.071957E+00	4.485010E+00	4.170346E+00

Annex 3

Basic statistics of equalized time series – 10-month lag

Statistics	1.MLP 30-6-1	2.MLP 30-3-1	3.MLP 30-5-1	4.MLP 30-9-1	5.MLP 30-7-1
Minimal predictions (Training)	9.581047E+07	8.978954E+07	9.523406E+07	8.620605E+07	1.226069E+08
Maximal predictions (Training)	1.143141E+09	1.169006E+09	1.128150E+09	1.156245E+09	1.152624E+09
Minimal predictions (Testing)	1.275041E+08	1.225674E+08	9.857046E+07	1.188153E+08	1.261200E+08
Maximal predictions (Testing)	1.142398E+09	1.163636E+09	1.069460E+09	1.144003E+09	1.085287E+09
Minimal predictions (Validation)	1.274159E+08	1.139746E+08	9.620851E+07	1.102632E+08	1.244502E+08
Maximal predictions (Validation)	1.124260E+09	1.155792E+09	1.050281E+09	1.166400E+09	1.092989E+09
Minimal residuals (Training)	-3.298498E+08	-3.663393E+08	-4.178500E+08	-3.515643E+08	-4.260971E+08
Maximal residuals (Training)	3.812593E+08	3.643545E+08	5.210952E+08	3.813481E+08	4.795802E+08
Minimal residuals (Testing)	-2.326371E+08	-2.291130E+08	-2.144975E+08	-2.476463E+08	-2.300545E+08
Maximal residua (Testing)	4.212896E+08	4.000518E+08	4.942276E+08	4.196847E+08	4.784008E+08
Minimal residuals (Validation)	-2.435260E+08	-2.420521E+08	-1.957826E+08	-2.076164E+08	-2.164618E+08
Maximal residuals (Validation)	1.888672E+08	1.813321E+08	3.057997E+08	1.845939E+08	2.816919E+08
Minimal standard residuals (Training)	-4.469026E+00	-4.922313E+00	-4.922472E+00	-4.724518E+00	-5.116134E+00
Maximal standard residuals (Training)	5.165556E+00	4.895644E+00	6.138750E+00	5.124770E+00	5.758303E+00
Minimal standard residuals (Testing)	-2.791572E+00	-2.759282E+00	-2.331060E+00	-2.998620E+00	-2.583201E+00
Maximal standard residuals (Testing)	5.055342E+00	4.817954E+00	5.371037E+00	5.081741E+00	5.371794E+00
Minimal standard residuals (Validation)	-3.274627E+00	-3.307242E+00	-2.799055E+00	-3.043960E+00	-3.104309E+00
Maximal standard residuals (Validation)	2.539645E+00	2.477603E+00	4.371944E+00	2.706417E+00	4.039783E+00