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**Article**

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Article

# Sanctions as a Catalyst for Russia's and China's Balance of Trade: Business Opportunity

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**Abstract:** Economic sanctions are among the most powerful instruments of international policy. However, this study, using the example of the so-called anti-Russian sanctions, shows that in the global economy, countries are rapidly using other alternatives, and sanctions in the case analyzed act as a catalyst for balance of trade between the Russian Federation and the People's Republic of China. The study is based on a highly topical sophisticated model of neural networks, which provides clear results confirming the unintended positive effect. The time series and aggregated data became inputs into multilayer perceptron networks, while the methodology used enabled eliminating of both too large averaging and extreme fluctuations of the equalized time series. Out of 10,000 networks created for each variable and each time lag, five showing the best characteristics given by correlation coefficients and absolute residual sums were retained. Thus, the created equalized time series were able to describe the basic trend of the actual development of export and import, while also capturing their local extremes. The interpolation of the two time series shows that the sanctions imposed on the Russian Federation in 2014 have clearly strengthened its balance of trade with the People's Republic of China. The results of the study also predict further growth in the balance of trade between the Russian Federation and the People's Republic of China, although this development may be delayed by current events.

**Keywords:** artificial neural networks; time series; import; export; restriction; international policy; financial market



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## 1. Introduction

Do sanctions imposed on a particular country in a global economy environment, in accordance with their intentions, act as a tool of diplomatic pressure, or can they have a significant incentive effect on the whole world? This is an issue that is largely addressed by both international diplomacy and a number of economic research studies, which serve precisely as a basis for final political decisions of global significance. Research on the effect of sanctions can be based on vector auto-regression modeling (VAR models), which were used to assess the impact of sanctions on Russia after 2014, such as by Dreger et al. (2016), and further developed by Kholodilin and Netšunajev (2019), using a number of multiple variables and indicators, headed by GDP (gross domestic product) growth rates, key commodity prices, and exchange rates. On the other hand, Boulanger et al. (2016) used the computable general equilibrium (CGE) model to determine the impact of economic pressure tools. Interestingly, while in the case of vector autoregressive modeling, Kholodilin and Netšunajev (2019) evaluated the effects of sanctions as relatively mild and without significant impact on the economic development, and the computable general equilibrium model created by Boulanger et al. (2016) showed an impact on the Russian economy worth 3.4 billion euros between 2014 and 2016.

Therefore, there is a clear need to use other modern methods of economic research, including the use of machine learning, which will provide us with the opportunity to verify the results achieved or expected so far, as well as the ability to more accurately quantify the

impact of these measures on selected areas of the economy. A specific area of research is therefore the impact of the so-called “anti-Russian” sanctions and their reciprocal measures on the balance of trade between Russia and the People’s Republic of China.

The history of these economic sanctions dates back to March 2014, when the Council of the European Union (EU) decided to ban visas for a group of 149 persons—citizens of the Russian Federation, for 37 persons who decided to freeze their assets in the EU (Ashton 2014). Subsequently, the EU decided to impose economic sanctions on the Russian Federation, and in March 2015, the Council linked their duration to the full implementation of the Minsk Agreements. The same measures were taken against the Russian Federation by the governments of the USA, Canada, Australia, and Japan. The Council took these measures on the basis of a decision designating the Russian Federation as a player responsible for activities that undermine or threaten the territorial integrity, sovereignty, and independence of Ukraine, and the Russian Federation responded reciprocally to these diplomatic and economic steps.

It is not possible to generalize the effects of economic sanctions, especially in the situation where all the effects are valid only for a specific place, time, and situation. In the given case, where the analyzed economic phenomenon is not exclusively limited to trade relations with countries applying economic restrictions, it is possible to predict their positive effect in terms of strengthening the balance of trade with another major trading partner (country) not directly involved in the sanctions imposed. In the case of Russia as one of the most important exporters of strategic commodities, especially hydrocarbons, a significant effort for economic diversification, the need for massive investment, and tax incentives associated with major partners who do not impose sanctions can be expected (Kapustin and Grushevenko 2019). This is one of the reasons why the balance of trade of the Russian Federation and China was chosen from the point of view of quantifying the impact of the above-mentioned sanctions.

In addition to the quantification of the impact of sanctions and other possible application of the resulting model in other political-economic decisions, its results also answer the question whether the so-called “super-partnership” of the two superpowers did actually happen, to the notified representative of the Russian Federation in connection with the sanctions adopted in 2014 (Baev 2016). Thanks to the use of exact machine learning methods, it is possible to separate the very influence of decisions of the Council of the EU and other countries and subsequent reciprocal measures from other economic influences within both countries. It is also important to compare the exact results with research into the subjective perception of the risks associated with imposing anti-Russian sanctions (Golikova and Kuznetsov 2016), which pointed to a significant level of concern especially for companies with higher import rates, which is up to 29.8% of the surveyed companies in the third phase of the mentioned research.

The objective of the paper is to use artificial neural networks to equalize the time series of mutual balance of trade of the Russian Federation and the People’s Republic of China in order to predict its future development and thus the impact of sanctions imposed on the Russian Federation by the EU and other countries. In order to achieve this result, the following questions must be answered:

- (1) Have the sanctions imposed on the Russian Federation strengthened the trade with the People’s Republic of China since 2014?
- (2) Can we expect mutual trade between these countries to grow in the future?

The following part of the paper contains the literary research focused mostly on both negative and positive impact of the sanctions and describes the advantages and disadvantages of individual methods applicable for the problem specified above. The section of Materials and Methods describes the data used, the selection of variables, and basic statistical characteristics of datasets, which is followed by the structure of the applied neural networks and the calculation procedure. In the Results part, the most suitable networks are selected and predictions made using the selected most suitable networks are presented. Discussion provides answers to the formulated research questions and compares

the results obtained with the results obtained by other researchers. The Conclusion part summarizes the results achieved, describes their application in practice and limitations of the research.

## 2. Literary Research

Are these significant measures that can change governments and have an impact on the global economy, or much fuss about nothing? The history of research into the impact of sanctions is as old as sanctions themselves. Their initiators always needed to have a qualified prediction of the expected impact and be able to predict real consequences of the measures taken. This is also related to a number of publications dealing with bilateral or multilateral restrictions. These can be divided into three areas. The first is research that deals with the general principles and laws of sanctions. [Amiri et al. \(2019\)](#) stated that in the case of countries rich in natural resources, the impact of sanctions on macroeconomic indicators needs to be assessed in terms of institutional quality. The assessment of sanctions in the geopolitical context is also important; [Gartzke and Westerwinter \(2016\)](#) showed that not only do political decisions affect economic restrictions, but there is also a significant impact of cross-border economic links that hinder the application of restrictions. This was also confirmed by [Shea and Poast \(2017\)](#), who dealt with the issue of conflict financing, where lack of finance or poor access to credit directly prevents escalation of conflicts. This was confirmed by [Mendoza et al. \(2019\)](#). According to them, local conflicts can also affect the global economy. The significant effect of economic sanctions was confirmed by [Wang et al. \(2019\)](#) on the example of 23 cases assessed in the period of 1996–2015 in the form of significantly increased exchange rate volatility, which indicates the importance of the balance of trade, which, however, is not directly addressed. Another problem is the assessment of the restrictions effect in the economic system, which is not fully deregulated. [Talipova et al. \(2019\)](#) dealt with the issue of market efficiency through Fam's theory, noting that in the environment that cannot take full advantage of the effects of the second best alternatives, the effects of sanctions are worse than in the case of fully market economic systems.

[Afesorgbor and Mahadevan \(2016\)](#) pointed to the time factor and different impacts examining the effects of sanctions on population income and analyzing the effect with respect to the duration of sanctions. According to the authors, the main effect consists in a significant increase in income inequalities, which is exacerbated over time. This was confirmed by [Neuenkirch and Neumeier \(2016\)](#), as well as by the conclusions of [Jeong \(2020\)](#). Moreover, the variables necessary for the complex evaluation of time series are not always fully available and relevant but there is, for example, a comparative analysis ([Biersteker et al. 2018](#)) using the data of the sanctions imposed by the UN Security Council, while the authors themselves do not consider all sanctions to be effective. [Chen et al. \(2019\)](#) examined aggregated data from thirty analyzed sanctions. In terms of effect, they evaluated multilateral sanctions more positively. There is also an unambiguous influence of the approach to sanctions, as described by [Early and Preble \(2020\)](#), who proved far greater intended effect in the case of fully enforced sanctions. Similarly, [Feldman and Sadeh \(2016\)](#) or [Sadeh and Feldman \(2020\)](#) pointed to the contradiction between the state official sanction policy and the interests of companies. [Shin et al. \(2016\)](#) compared 133 sanctions from the perspective of macroeconomic indicators. Broader economic impact of sanctions was addressed by [Early and Peksen \(2019\)](#). They used global quantitative analysis to prove that the effects of restrictions are visible not only on standard indicators but also lead to significant growth in the "grey" economy.

In general, it can be stated that it is an extremely large area, which, however, provides only a theoretical background for sanction initiators' decision-making, which may have globally significant economic effects. These are addressed in the second research concerning the prediction or analyses of the impacts of sanctions on the entity in question. This does not have to include geopolitical conflicts. For example, according to [Góis et al. \(2019\)](#), the most effective approach to the climate protection is a combination of sanctions and

rewards. However, sanctions are more common in terms of conflicts. These can include relatively less important conflicts, which, however, have global impacts as in the case of assessing the impacts of embargo imposed on Chinese imports of global maize price. According to [Schmitz \(2018\)](#), this caused a 1.24% drop in the price of this commodity in the world markets in 2013. [Gholz and Hughes \(2019\)](#) mentioned the example of assessing Chinese embargo on exporting precious metals to Japan in 2010. They drew attention to poor consideration of the market dynamics and the resulting low efficiency of the sanctions, where an insufficient analysis results in low efficiency of the restriction and the positive impact of the balance of trade with third parties. [Gowa and Hicks \(2017\)](#) demonstrated this effect on the example of World War I, when the cessation of trade between the parties directly involved in the conflict was, from the participants' perspective, not as important a step as expected by using the effect of the second best alternatives. The positive impact of sanctions on the development of trade relations with third parties was quantified by [Seyfi and Hall \(2019\)](#) specifically for tourism. [Early and Jadoon \(2016\)](#) saw unambiguously positive effects in the analyzed cases. They analyzed the unintended impacts of sanctions on the example of restrictions imposed by the United States between 1960 and 2000. [Afesorgbor \(2019\)](#) explained the positive effects of sanctions. According to him, the positive effect is triggered by increasing the level of stock and by intensifying trade relations in view of the expected impact before the restrictions come into force.

The third important area of current research is the expected and analyzed impact of sanctions with global importance, most often called "anti-Iranian" and "anti-Russian". Their common feature is mainly their impact on global hydrocarbon prices. [Gharehgozli \(2017\)](#) believed in the negative impact of "anti-Iranian" sanctions on a target country. He mentioned the impact of 17% GDP. In the case of Russia, [Charap et al. \(2017\)](#) stated that for Russian foreign and economic policy, the economic restrictions in 2014 were a turning point, radically accelerating the existing trends. According to [Dudlák \(2018\)](#), who pointed mainly to the stabilization of oil prices, the expected quantification of the "anti-Iranian" sanctions mitigation is an example of predictive analysis.

The effects of "anti-Russian" sanctions were discussed by [Baev \(2016\)](#), who examined the expansion and strengthening of trade relations between the Russian Federation and the PRC as a response to anti-Russian sanctions from the perspective of a complex question of a global character. [Connolly \(2016\)](#) assessed the economic effects of sanctions, including the unintended ones. According to the author, sanctions often have also unintended effects both for the economy and for the political scene. Similar results were obtained by [Skalamera \(2018\)](#) within the analysis of the causes and reasons that in 2014 led to signing an intergovernmental contract for the supply of 38 billion cubic meters of natural gas for the period of thirty years. [Mau \(2016\)](#) comprehensively analyzed the economic situation of Russia in 2014–2016. According to the author, the situation was defined by two key factors: external factors including the economic sanctions and the reduction of commodity prices. [Ankudinov et al. \(2017\)](#) dealt with the positive effects of sanctions on selected industries of the national economy, analyzing their impact on Russian capital market through distribution methods (tail index). [Fedoseeva and Herrmann \(2019\)](#) dealt with the issue of separating other factors affecting the mutual balance of trade in connection with the sanctions and restrictions between the Russian Federation and Germany, stating that the real effect was smaller than expected. On the contrary, [Tuzova and Qayum \(2016\)](#) analyzed the impact of sanctions on the exchange rate of important commodities in Russia through vector auto-regression models, while [Pak and Kretzschmar \(2016\)](#) dealt with the impact of sanctions on the individual industries in the same country. In both cases, the increase in the volatility was stated without an unambiguously negative result for the target country. [Giumelli \(2017\)](#) examined the issue of the impact of sanctions on the initiators of "anti-Russian" sanctions. According to the author, the evident global negative impact on the EU countries has also a positive effect on selected industries. Through the analysis of individual EU countries' export by the Standard International Trade Classification (SITC 22), countries such as Greece, Sweden, Luxembourg, and Bulgaria could benefit from the

sanctions imposed. [Kwon \(2020\)](#) showed negative impact on the initiators. According to the author, a strongly restrictive policy towards South Korea and Japan had a direct negative impact on the People's Republic of China.

In terms of this research, it is difficult to separate the influence of sanctions imposed on Russia on the official policy of the People's Republic of China, which, according to [Esen and Oral \(2016\)](#), strives primarily for ensuring the energy needs of the country, as well as of other important consumers. These Chinese efforts focused on two directions of the development were described by [Zhao et al. \(2019\)](#). [Du and Zhang \(2018\)](#) used regression methods for their quantification and evaluate the effects of the initiative "Economic Silk Road" on Chinese mergers and acquisitions abroad through the difference-in-difference (DD) model. [Strange et al. \(2017\)](#) used the methodology for evaluating Chinese investments. The same issue was investigated by [Bradshaw and Waterworth \(2020\)](#), according to whom the sanctions and other restrictions imposed on Russia represent only one of many economic and geopolitical factors.

[Røseth \(2017\)](#) directly highlighted the impact of sanctions in Russian and Chinese mutual trade. The author considered the sanctions an important catalyst accelerating Russian orientation on China in terms of oil and natural gas supplies. The author's work was primarily focused on carbohydrates, not on assessing the volume of export. An interesting fact is that compared to the expected Russia's interest in the diversification of commodity markets and securement of investments in order to strengthen the key industries, [Du and Zhang \(2018\)](#) stated that the energy sector has fallen from first to fourth place in the ranking of five selected industries. This opens a discussion about the difference between the expected positive effect of sanctions on the balance of trade and the actual volume of Chinese investments in the Russian Federation. [Fortescue \(2015\)](#) provided a partial explanation stating that sanctions were not a decisive factor for Russian orientation "to the east", as the given process had started before the sanctions were imposed. However, at the same time, the author stated that the restrictions imposed by several Western countries were an impulse for strengthening economic and political relationship of the Russian Federation and Asian-Pacific region.

The research on the effects of sanctions is relatively complex. The most commonly used methods include vector auto-regression modeling, used e.g., by [Nasir et al. \(2018\)](#) or [Kholodilin and Netšunajev \(2019\)](#). In some cases, the method used provides too large variances of achieved values; these models also show difficulties in assessing the distracted data and data based on the values of grey economic or the results outside reported international indicators. These problems can be avoided by using machine learning.

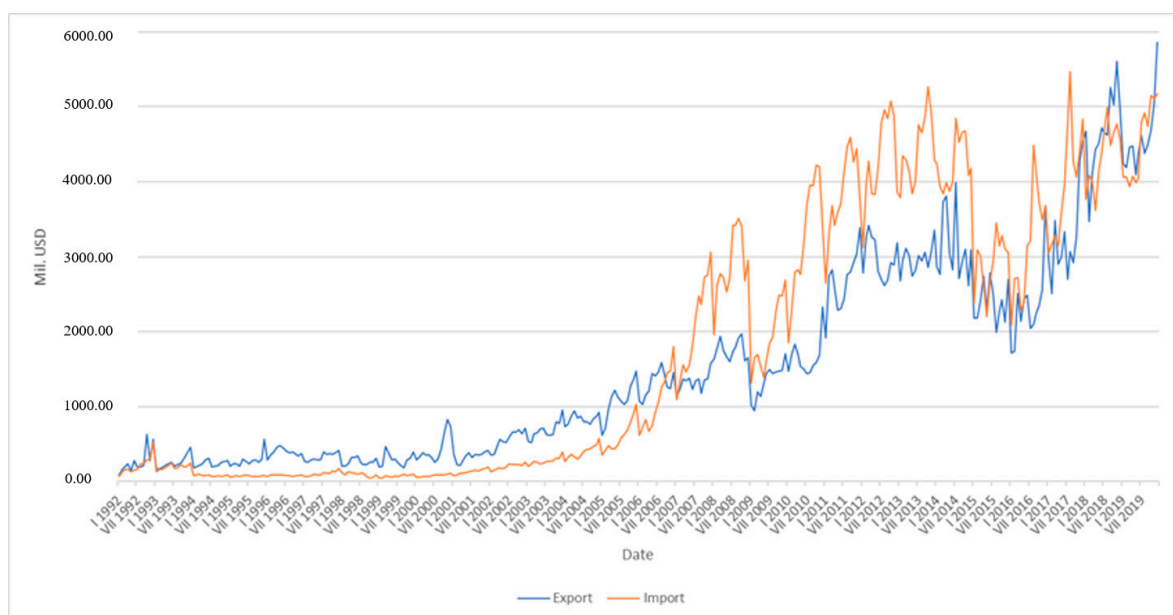
[He et al. \(2017\)](#) used neural networks for evaluating the correlation of the economic and stimulation measures with the environment. [Ekinci and Erdal \(2017\)](#) presented machine learning bankruptcy models. In their study, which has a direct impact on the analyzed issue, [Vochozka and Vrbka \(2019\)](#) effectively used machine learning for mapping and identification of the correlation in the context of the EUR and Yuan exchange rate. [Rousek and Mareček \(2019\)](#) developed a methodology that takes into account time series seasonal fluctuations by means of artificial neural networks in the case of the USA export to the People's Republic of China. [Vochozka et al. \(2020a\)](#) successfully used artificial neural networks to determine to what extent the fluctuations in oil prices influence the value of Euro to the value of USD. [Vochozka et al. \(2020b\)](#) used artificial neural networks to create a methodology for the prediction of a company failure. [Šuleř and Machová \(2020\)](#) used artificial neural networks for predicting future development of share prices; [Vochozka and Machová \(2018\)](#) used them for identifying the value drivers of a transport company. [Scheidegger and Billionis \(2019\)](#) presented the GPR method for dynamic stochastic economic models in the irregular shape of state space. However, they do not apply the model in the issue of the impact on balance of trade. On the contrary, [Carmona et al. \(2019\)](#) used machine learning for the quantification of economic effects. They used a new machine learning algorithm for predicting the failure of individual elements of the USA banking sector. For the application of the analytic method of machine learning, it is important to assess the setting of a relevant

neural network, especially the risk elimination consisting in insufficient volume of data as well as the risk of its “overfitting”. This is addressed by [Belkin et al. \(2019\)](#) in the description and uniform curve of the relevant network performance.

As mentioned above, this contribution will examine sanctions in relation to the macroeconomic variables, i.e., specifically with the export and import indicators. The reason for choosing these indicators is their important role they have in the whole economy. This is confirmed by [Kushniruk and Ivanenko \(2017\)](#), who argued that international economic relations in terms of export and import of goods and services have a significant impact on the development of economy of each country. According to [Bloom et al. \(2016\)](#), in this context, international trade on average has a positive impact especially on technological changes and innovations of domestic companies and enhances the aggregated growth of industry productivity. [Huang \(2020\)](#) also stated that export and import indirectly transmit information, technologies, and demands between individual economies. The author further added that export and import contribute to balancing markets and elimination of disparities in the world. Moreover, according to [Gladkov \(2016\)](#), increase in the volume of export contributes to increasing employment in domestic economy.

### 3. Materials and Methods

The mutual trade relations of the Russian Federation (RF) and the People’s Republic of China (PRC) have intensified in recent years, as evidenced by [Figure 1](#).



**Figure 1.** Development of RF and PRC export and import between January 2000 and July 2019 (from the point of view of RF); Note: The values in the entire text are given in USD million (Source: [International Monetary Fund 2020](#)).

The figure and the data set show the course of the time series at monthly intervals from January 1992 to December 2019. The figure shows the fluctuations within the individual years of the monitored period. However, the question is whether those are regular seasonal fluctuations or random fluctuations caused by imperfect long-term trade relations between Russian and Chinese trade partners. There is a relatively large increase in the volume of Russian goods exported to the PRC. The smallest volume of export, less than USD 93 million, was recorded at the beginning of the course of the time series, that is, in January 1992, while the largest volume of export was in December 2019 (more than USD 5860 million). By contrast, the smallest volume of import was achieved in January 1999 (less than USD 43 million), while the largest volume of goods imported from China to Russia was achieved in August 2017 (more than USD 5472.5 million).

The input variable for creating the model of equalizing time series (import and export) is time. In this case, there are available monthly values of the variable examined. This means that the values of export and import as of the last day of each calendar month are known. To be able to create a valid model, it is necessary to capture the development trend of the time series in the monitored period as well as within the individual years (i.e., seasonal fluctuations). The input variable is thus year expressed as a continuous variable. The correction will be carried out at the level of the shortest period of the monitored output variable, i.e., at the level of calendar month. There are basically two options. Month can be seen as a continuous variable; in such a case, Statistica's software settings will be used (used e.g., by MS Excel or Mathematica). This means that the date is converted into the number of days from 1 January 1900. To each input value, one value of output variable will be assigned. This way, however, seasonal (repeated in a certain period) fluctuation will not be identified. Month will thus be seen as a categorical variable and will be referred to by the name of the specific month. This enables assigning the values of several years and thus identifying seasonal fluctuations (Vochozka et al. 2019). The input variable will thus be the year of reporting the input variable (as a continuous variable) and the month of reporting the output variable (as a categorical variable).

Regression will be carried out using neural structures. Multilayer perceptron networks (MLP) will be generated.

Artificial neural networks are described in the previous part of the article. In general, they represent one of the computational models used in artificial intelligence. Artificial neural networks are a structure intended for a distributed parallel data processing. The structure consists of artificial neurons, whose biological model is a neuron. Neurons are interconnected and transmit signals to each other and transform them by specific transmission functions. The neuron can have any number of inputs but only one output. A general model of a neural network is described as follows:

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

where  $x_i$  are the inputs of the neuron,  $w_i$  are synaptic weights,  $\theta$  is a threshold,  $S(x)$  is a function of neurons transmission (activation function),  $Y$  is a neuron's output.

In terms of practical application, MLP networks are one of the most widely used types of neural networks, feed-forward neural networks with adjacent layers of neurons and weights. They provide a general framework for the representation of non-linear mapping between inputs and outputs. A typical MLP consists of a set of neurons representing an input layer, one or more hidden layers, and a set of output neurons.

The analytical function of MLP neural networks can be described as follows:

$$a_j = \sum_{i=1}^d w_{ji}^{(1)} x_i + w_{j0}^{(1)}. \quad (2)$$

The output of the  $j$ th layer is obtained first by creating a weighted linear combination of the input values  $d$ , with added bias. Here,  $w_{ji}^{(1)}$  is a weight in the first layer connecting the input with the hidden layer  $j$ , and  $w_{j0}^{(1)}$  is a bias for the hidden layer  $j$ . By incorporating a special input variable  $x_0$ , whose value is fixed at  $x_0 = 1$ , it is possible to modify the conditions of the bias for hidden layers. Analytically, this can be illustrated by the modification of Formula (2) into the following form:

$$a_j = \sum_{i=0}^d w_{ji}^{(1)} x_i. \quad (3)$$

The activation of the hidden layer  $j$  is achieved by the transformation of the linear sum by means of the activation function  $g(\cdot)$  as follows:

$$z_j = g(a_j). \quad (4)$$



The outputs of the network are obtained by transforming the activation of the hidden layer using the second layer of the processed elements. For each input layer, a linear combination of the hidden layer inputs is created in the following form:

$$a_k = \sum_{j=0}^M w_{kj}^{(2)} z_j + w_{k0}^{(2)} \tag{5}$$

Even in this case, the bias can be incorporated in the weights, which results in the following formula:

$$a_k = \sum_{j=0}^M w_{kj}^{(2)} z_j. \tag{6}$$

The activation of the *k*th input layer is achieved by the transformation of this linear combination using the non-linear activation function determined by the following relationship:

$$y_k = g(\tilde{a}_k). \tag{7}$$

By combining the Formulas (3), (4), (6) and (7), an explicit formula for the complete function of the network will be obtained:

$$y_k = \sum_{j=0}^M \left[ w_{kj}^{(2)} g\left(\sum_{i=0}^d w_{ji}^{(1)} x_i\right) \right]. \tag{8}$$

It shall be noted that shall the activation functions for the input layer are considered linear, i.e.,  $\tilde{g}(a) = a$ ; this functional form is a special case of a generalized linear discriminant function, where the basic functions are given by specific functions  $z_j$  defined in the Formulas (3) and (4). The crucial difference consists in the fact that in this case, the weights parameters in the first layer of the network as well as the parameters in the second layer shall be considered adaptive so that their values could change during the networks training process (Bishop 1995).

MLP can be calculated using the following formula:

$$y_k^n = f(w_{0,k}^n + \sum_{i=1}^m y_i^{n-1} * w_{i,k}^n). \tag{9}$$

The output of the *k*-th neuron in the *n*-th hidden or output layer.  $f(x)$  is a function of the neurons transmission,  $w_{0,k}^n$  is a neuron bias, *m* is the number of neuron weights.

A total of three sets of artificial neural networks differing in accordance with the time series time lag considered will be generated:

1. 1-month lag in the time series,
2. 3-month lag in the time series,
3. 6-month lag in the time series.

Time series lag indicates the amount of data from which the following value is calculated (that is, on the basis of the value of a previous month in the first case, on the basis of the values in previous three months—a quarter in the second case, and on the basis of the six previous months—a half-year in the third case). Longer lag can indicate the values averaging, while shorter lag can result in extreme fluctuations of the equalized time series. Time series lag thus does not represent an analysis of the time series seasonal fluctuations. It only indicates the complexity of the calculation of the predicted value and the number of inputs for each calculation. Each time series lag means higher demands on the complexity of the artificial neural structure, in particular, the neurons in the input layer (in Experiment 1, the input layer contains 13 neurons<sup>1</sup>, 39 neurons in Experiment 2, and 78 in Experiment 3). Other setting in the experiments are identical.

Seasonal fluctuations can be examined by determining the trend of the time series development, that is, by appropriate setting of input variables. The continuous independent variable will be a year. Seasonal fluctuation will be represented by categorical variable

<sup>1</sup> As shown below, one neuron will represent the continuous variable in the form of the year of the measurement, 12 neurons will represents the months in which the values were measured.

in the form of the month in which the value was measured. We will thus work with a possible monthly seasonality of the time series. As the overall trend of the time series shall be captured, the dependent variable will be the export and import of the RF to and from the PRC.

The time series is divided into three datasets—training, testing, and validation. The first set contains 70% of the input data. The training data set will be used for generating neural structures. The remaining two datasets contain 15% of the input data each. Both sets will be used for the verification of the reliability of the neural structure or the model found.

Table 1 shows the basic statistical characteristics of the dataset.

**Table 1.** Basic statistical characteristics of examined dataset.

Samples	Year (Input)	Export (Target)	Import (Target)
Minimum (Train)	1992.000	92.760	42.790
Maximum (Train)	2019.000	5860.110	5472.530
Mean (Train)	2005.504	1539.326	1821.468
Standard deviation (Train)	8.085	1358.751	1815.649
Minimum (Test)	1993.000	173.400	62.960
Maximum (Test)	2019.000	5028.780	4844.440
Mean (Test)	2005.880	1516.249	1741.595
Standard deviation (Test)	8.019	1320.065	1728.356
Minimum (Validation)	1992.000	145.860	44.730
Maximum (Validation)	2019.000	4473.790	5081.240
Mean (Validation)	2005.100	1439.480	1543.822
Standard deviation (Validation)	11.680	1193.594	1423.217
Minimum (Overall)	1992.000	92.760	42.790
Maximum (Overall)	2019.000	5860.110	5472.530
Mean (Overall)	2005.500	1521.034	1768.266
Standard deviation (Overall)	8.090	1349.768	1793.636

Source: Author.

A total of 10,000 neural networks will be generated, out of which 5 with the best characteristics will be retained<sup>2</sup>. As the error function, the function of least squares will be used, defined as follows:

$$E_{SOS} = \frac{1}{2N} \sum_{i=1}^N (y_i - t_i)^2, \tag{10}$$

where  $N$  is the number of the trained cases,  $y_i$  is the predicted target variable  $t_i$ ,  $t_i$  is the target variable of the  $i$ -th case.

The hidden layer will contain from three to 30 neurons. Table 2 shows the considered distribution functions in the hidden and output layers.

**Table 2.** Activation function of hidden and output layer of Multilayer perceptron (MLP) network.

Function	Definition	Range
Identity (Linear)	A	$(-\infty; +\infty)$
Logistic sigmoid	$\frac{1}{1 + e^{-a}}$	$(0; 1)$
Hyperbolic tangent	$\frac{e^a - e^{-a}}{e^a + e^{-a}}$	$(-1; +1)$
Exponential	$e^{-a}$	$(0; +\infty)$
Sine	$\sin(a)$	$[0; 1]$

Source: Author.

Other settings will remain default (according to the ANN tool—automated neural networks).

<sup>2</sup> Least squares method will be used. Networks generating will be terminated if there is no improvement, that is, if the sum of squares is not reduced. We will thus retain only those neural structures whose sum of residual squares to the actual export of the RF to the PRC is as low as possible (zero in ideal case).

The expected analysis outputs will be as follows:

- Overview of the retained networks: in each case, it contains the structures of five retained neural networks, performance of the datasets, error function, function of the activation of the neural network hidden and output layers.
- Correlation coefficients: characterize the network performance in the individual data subsets.
- Basic statistics of equalized time series.

Based on the correlation coefficients and the sum of the absolute residuals, the most suitable neural networks will be selected for both export and import, which enables us to describe their ability to equalize time series and thus predict the further development of the variables. The following results will thus apply only to the selected networks (those with the best characteristics):

- Graph of equalized time series.
- Predicted values from January 2020 and December 2021.
- Graph of the actual time series development with the predictions, that is, a possible development of the time series from January 1992 to December 2021.

#### 4. Results

The output of the methodology applied is 10,000 MLP networks for each variable and each time lag. For each part of the experiment, five artificial neural networks were retained. Their overview and statistical characteristics of the equalized time series are presented in Appendix A. The overview shall contain the following:

- Structure of the neural network in the following form: serial number of the neural network retained from the experiment, designation of the neural network type (MLP), number of neurons in the input layer and output layer. The objective is to predict the result—either import or export. Therefore, the output layer always contains only one neuron.
- Neural network performance: it is the value of the correlation coefficient indicating the result of equalizing the time series by the neural network (or to which extent the actual and equalized time series' course are identical). The performance is given separately for the training, testing, and validation datasets.
- Error of neural network.
- Training algorithm: in all cases, the Broyden–Fletcher–Goldfarb–Shanno training algorithm (Avriel 2003) is used.
- Error function: Statistica software will choose either entropy or sum of least squares.
- Activation function of the hidden layer of neurons.
- Activation function of the output neuron.

The second table shows the basic statistical characteristics (minimum, maximum, residuals, square residuals, absolute residuals, etc.) of equalized time series. The data sets are divided into training, testing, and validation subsets

##### 4.1. Selection of Most Suitable Networks

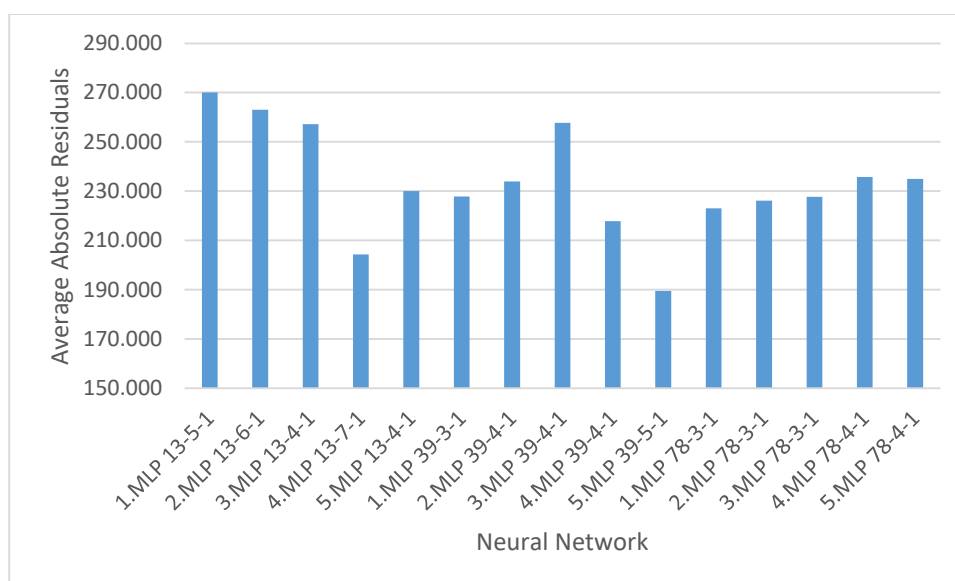
As follows from the methodology, it is necessary to choose the most suitable neural network which is able to describe the monitored variables, simplify the reality, and create a model that would help to predict the development of the RF and the PRC export and import. Absolute residuals were chosen as the characteristics according to which the most suitable neural network and thus the best prediction tool will be selected. As we worked with three different time lags, it is necessary to consider the missing data of the equalized time series corresponding to the relevant time series lag. We thus shall work with the average values of the absolute residuals. Table 3 compares the characteristics of the sum of absolute residuals and the average of absolute residuals of the equalized export time series.

**Table 3.** Comparing absolute residuals of equalized time series.

Neural Network Equalizing the Export Time Series	Absolute Residuals	Average Absolute Residuals
1.MLP 13-5-1	90,463.533	270.040
2.MLP 13-6-1	88,100.067	262.985
3.MLP 13-4-1	86,168.063	257.218
4.MLP 13-7-1	68,463.937	204.370
5.MLP 13-4-1	77,062.563	230.038
1.MLP 39-3-1	75,867.255	227.830
2.MLP 39-4-1	77,909.645	233.963
3.MLP 39-4-1	85,808.995	257.685
4.MLP 39-4-1	72,553.107	217.877
5.MLP 39-5-1	63,135.839	189.597
1.MLP 78-3-1	73,588.614	222.996
2.MLP 78-3-1	74,619.158	226.119
3.MLP 78-3-1	75,161.585	227.762
4.MLP 78-4-1	77,786.433	235.716
5.MLP 78-4-1	77,536.134	234.958

Note: MLP i-j-k: MLP indicates the type of the most suitable neural network (multilayer perceptron neural network; *i* indicates number of neurons in input layer—number of variables; *j* indicates number of neurons in hidden layer; *k* indicates number of neurons in output layer). Source: Author.

The table shows that the most successful neural network is the 5. MLP 39-5-1, a neural network created with a quarter’s time lag. The average absolute residual is 189.597. The graph in Figure 2 shows the differences between the networks.



**Figure 2.** Comparing average absolute residuals of equalized time series of RF export to PRC (Source: Author).

On the basis of the comparison, it can be concluded that the time series was best equalized by the network 5. MLP 39-5-1. In further prediction of the development of the RF export to the PRC, we will work with this network.

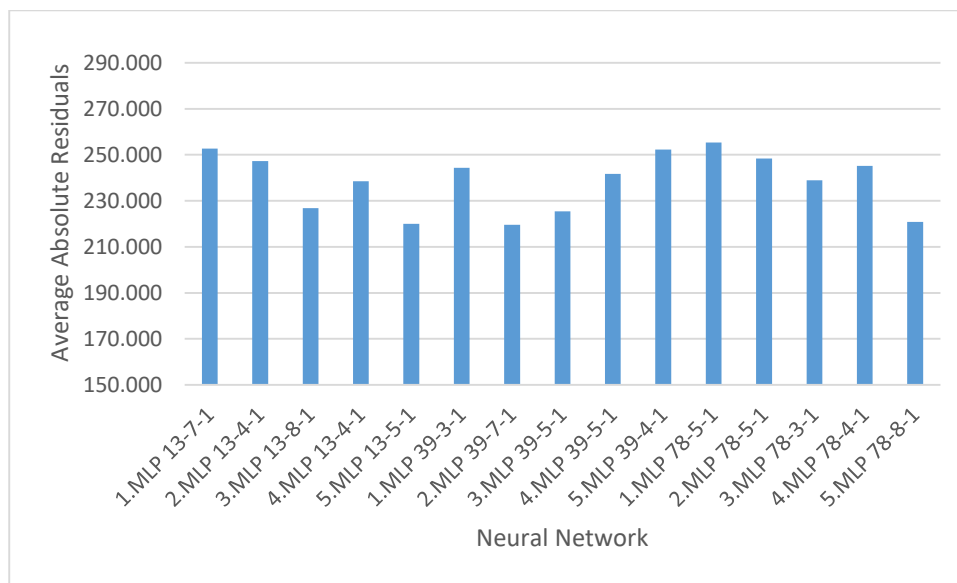
The same procedure was applied in the case of the RF import from the PRC. Table 4 compares the sum of the absolute residuals and average absolute residuals of the equalized import time series.

**Table 4.** Comparison of average absolute residuals of equalized time series of RF import from PRC.

Neural Network Equalizing the Export Time Series	Absolute Residuals	Average Absolute Residuals
1.MLP 13-7-1	84,659.737	252.716
2.MLP 13-4-1	82,844.840	247.298
3.MLP 13-8-1	75,969.699	226.775
4.MLP 13-4-1	79,909.030	238.534
5.MLP 13-5-1	73,711.346	220.034
1.MLP 39-3-1	81,368.085	244.349
2.MLP 39-7-1	73,128.771	219.606
3.MLP 39-5-1	75,067.048	225.427
4.MLP 39-5-1	80,507.543	241.764
5.MLP 39-4-1	84,015.830	252.300
1.MLP 78-5-1	84,270.077	255.364
2.MLP 78-5-1	81,965.733	248.381
3.MLP 78-3-1	78,856.170	238.958
4.MLP 78-4-1	80,889.255	245.119
5.MLP 78-8-1	72,859.601	220.787

Source: Author.

As in the previous case, the graph in Figure 3 was used for clear representation.

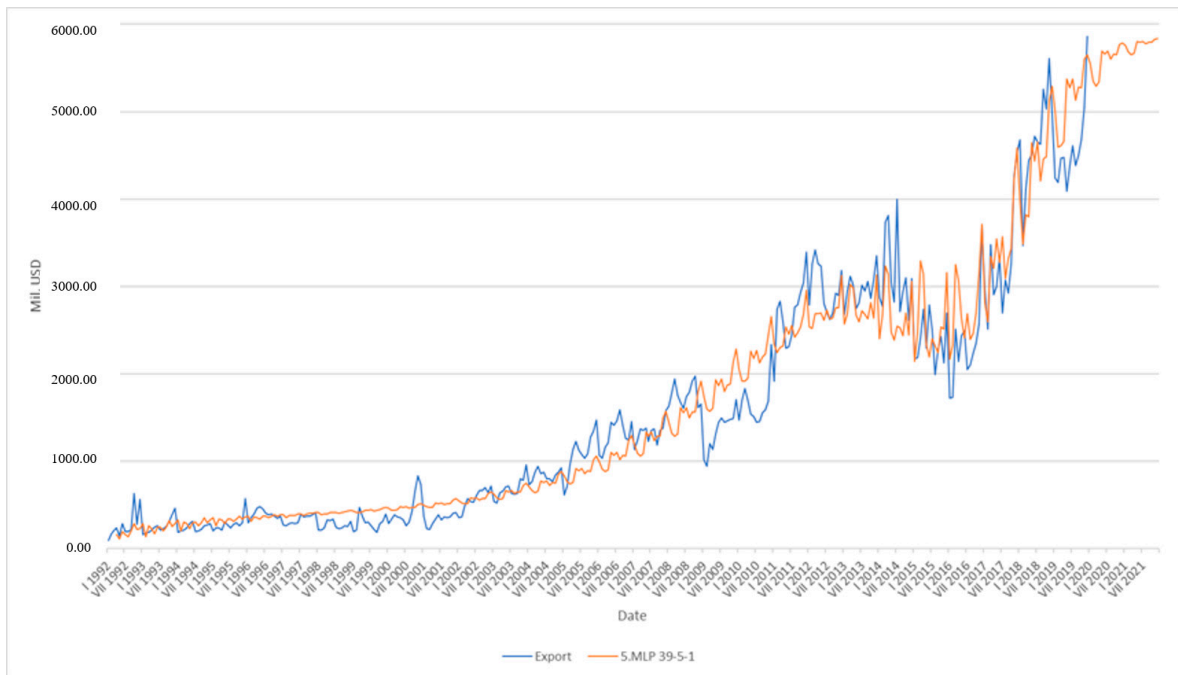


**Figure 3.** Comparing absolute residuals of equalized time series of RF import from PRC (Source: Author).

The best results are achieved by the network 2. MLP 39-7-1, which will subsequently be used for predicting the future development of the RF import from the PRC. This network also used the results of the previous three months for the calculation of each value.

#### 4.2. Prediction

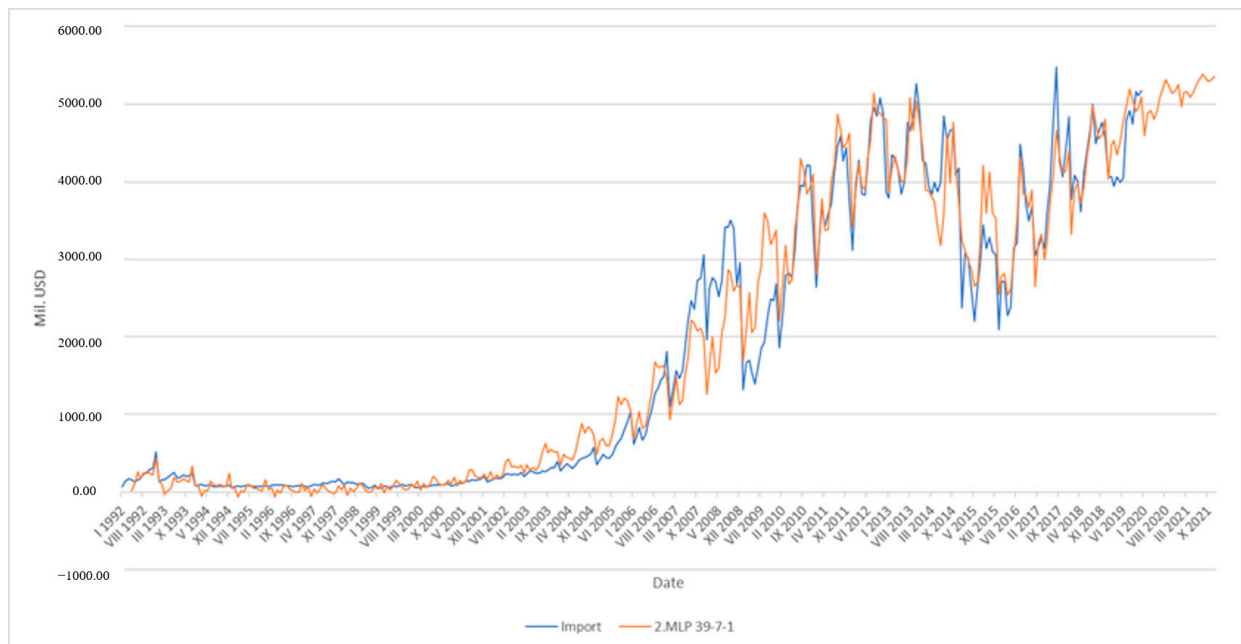
The graph in Figure 4 shows the comparison of the actual course of the export and equalized time series using the 5. MLP 39-5-1 network.



**Figure 4.** Comparison of export and equalized time series of RF export to PRC with prediction until December 2021 (Source: Author).

It follows from the figure that the equalized time series is able to describe the basic trend of the actual export development and is also able to capture the local extremes of the time series to a large extent. This indicates a great potential of the neural network to make quality and relatively accurate predictions.

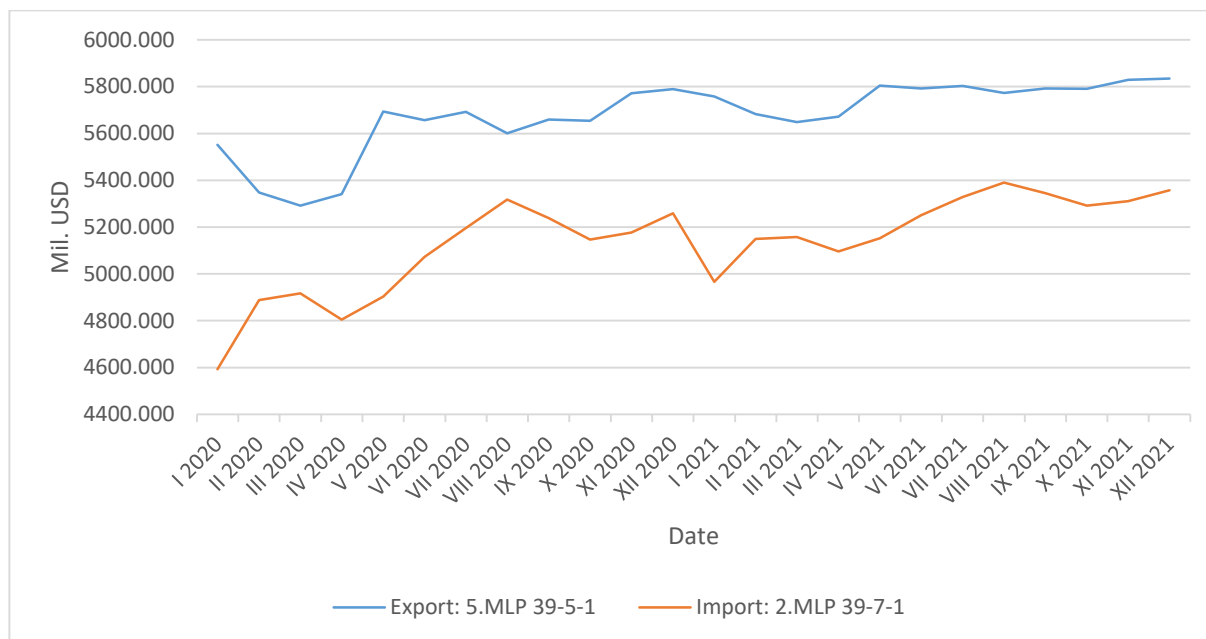
Another step was to compare the import time series with the most successful network in this part of the experiment, specifically the network 2. MLP 39-7-1 (for more details, see Figure 5).



**Figure 5.** Comparison of export and equalized time series of RF import from PRC with prediction until December 2021 (Source: Author).

In this case, the neural network clearly describes the basic trend of the time series, being even able to capture the majority of the local extremes of the RF import from the PRC.

Figure 6 shows the prediction of the RF and PRC trade (from the perspective of the RF) for the period of January 2020–December 2021.



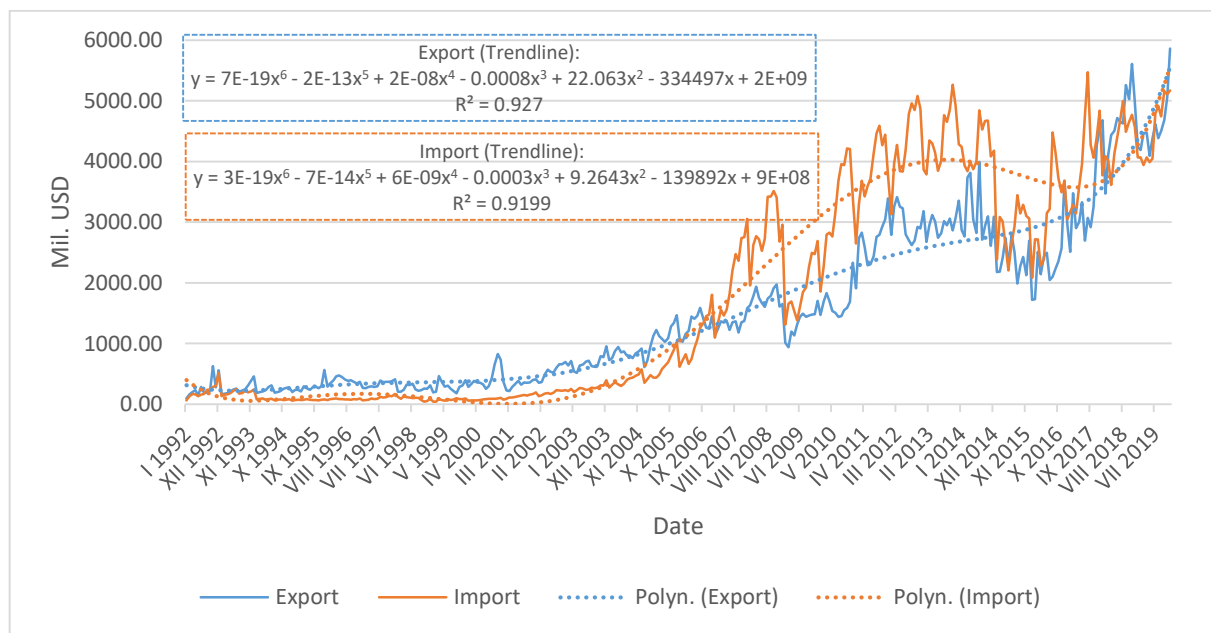
**Figure 6.** Development of mutual trade of RF and PRC between January 2020 and December 2021 (Source: Author).

## 5. Discussion

The research conducted clearly answers the question whether and how the sanctions imposed on the Russian Federation in 2014 have affected the balance of trade with the People's Republic of China.

There is no doubt that some producers tend to diversify their outlets and customers in order to increase the profitability of their product or to secure themselves financially in the event of losing some of them or retroactively. Some customers are clearly interested in increasing the number of real or potential suppliers, regardless of the external environment and the conditions that might or might not be limited by trade barriers, which include sanctions, and regardless of the fact whether it is a microeconomic phenomenon at a level of company or macroeconomic phenomenon on the global scale. It is possible to see the development of the mutual trade, especially in the area of the Russian Federation import from the People's Republic of China even before the sanctions are in force, and a possible influence of expected restrictions immediately before they are imposed remains a question. As Figure 7 shows, the subsequent development clearly confirms a significant impact the sanctions have on the development of both countries' trade relations.

The fitting of the time series with a trend shows a converging trend with the increasing value of the mutual trend. The fitting is relevant, since the coefficient of determination achieves the values above 0.9 in both cases, while the curve is a polynomial of degree 6. Its shape is evident and corresponds to the continuous growth of the phenomenon monitored. The applied method is also able to remove the seasonal fluctuations, which even increases the value of the model solution.



**Figure 7.** Export and import with significant impact of sanctions on development of trade relations (Source: Author).

Time series equalizing also provides answers to some of the questions brought up by further research. It could be seen that political announcements made by major representatives of the Russian Federation concerning the higher orientation of the country towards Asian regions have been fulfilled to a certain extent, with a clear time lag. The temporary recorded short-term decrease in the import shortly after imposing the sanctions, followed by the same decrease in the case of export and then by a sharp growth, is probably linked to the time lag between the announcement and the implementation as well as the temporary effect of the sanctions consisting in the necessity to ensure a new financial capital.

The method used also provides the answer to the second research question. The time series and all aggregated data became the inputs for MLP networks with a different time lag. The aim was to achieve a result that would minimize the averaging and extreme fluctuations of the equalized time series. The independent variable was a calendar year, which also captures the overall trend. The dependent variable is the export and import between the Russian Federation and the People's Republic of China.

The output of the methodology applied was 10,000 MLP networks for each lag and each variable. The time lag caused a relative complexity of the structure, where in Experiment 1, the input layer contained 13 neurons, while in Experiment 2, there were 39 neurons, and 78 neurons in Experiment 3. Each neuron represents a continuous variable in the form of the year of the measurement, 12 neurons mean months in which the values were measured.

Out of the 10,000 networks, 5 with the best characteristics given by the correlation coefficients and sum of absolute residuals, that is, those achieving the highest efficiency in equalizing time series and able to predict further development of variables, were retained. This model assumes that the Russian Federation export to the People's Republic of China will grow in the determined period up to more than USD 5800 million per month in the two following years, and the import will grow to nearly USD 5400 million.

Neural networks were able to express the principles of both time series very precisely and were able to equalize them. It showed that neural networks are able to effectively predict the future development of mutual export and import of the Russian Federation and the People's Republic of China. This corresponds with the results of the research conducted by Rowland et al. (2019), whose aim was to compare the accuracy of the harmonization of time series on the example of the Czech Republic and the People's Republic of China balance of trade by means of regression analysis and neural networks. The research results



indicate that the LOWESS curve (locally weighted scatterplot smoothing) and the network RBF 1-24-1 appear to be the most suitable for this purpose. [Vrbka et al. \(2019\)](#) expressed a very similar attitude. Their objective was the same as in the case of the research mentioned above but was carried out on the example of the EU and the People's Republic of China balance of trade. In terms of linear regression, the most suitable one was the LOWESS curve; in terms of neural networks, three out of five networks were retained which turned out to be applicable in practice—2. RBF 1-29-1, 3. RBF 1-29-1, and 5. RBF. The objective of the research conducted by [Rousek and Mareček \(2019\)](#) was to propose a methodology that would consider seasonal fluctuations in equalizing time series by means of artificial neural networks on the example of the USA export to the People's Republic of China. For the purposes of the research, the data from the period of January 1985–August 2018 were used. For predicting, two types of neural networks and two variants of the input data sets were used. In the second variant, seasonal fluctuations were represented by categorical variable. It was concluded that all retained structures are applicable but MLP networks of variant B achieve better results. [Narayan \(2006\)](#) used a slightly different approach when examining China's balance of trade and real exchange rate vis-à-vis the USA. Through the boundary-value testing approach to co-integration, the author found evidence that China's balance of trade and real exchange rate vis-à-vis the USA are co-integrating. Using the autoregressive model of distributed time lag, the author also found that in the short and long-term, devaluation of the Chinese RMB improves the balance of trade. The method of co-integration, which proved to be very successful, was also used in the research conducted by [Hamori \(2009\)](#), who focused on the long-term relationship between export and import.

The research did not answer current questions about the economic impact of the spread of COVID-19, as well as the continuing disagreement between OPEC (Organization of the Petroleum Exporting Countries) members and other major oil producers on the volume of their production. These two factors should not be perceived as pure negatives in relation to the growth of the balance of trade; it will depend on their impact on the economies of both powers, and they both are rather of a temporary nature. Therefore, it is likely that the balance of trade will reach the predicted state, while the possible time lag will depend on the impact and importance of these factors. An interesting variation of the development would then be abolition or easing of sanctions by their original initiators, for example, as a result of a complex effort to revive the economic development disrupted by the COVID-19 disease. However, even in such a case, the prediction of the development is so robust that it still indicates a growth of both countries' balances of trade.

## 6. Conclusions

The objective of the paper was equalizing the time series of mutual balance of trade between the Russian Federation and the People's Republic of China using the artificial neural network in order to predict its future development and thus the impact of sanctions imposed on the Russian Federation by the EU and other countries.

To achieve the objective of the paper, artificial neural networks were selected, specifically multilayer perceptron networks and radial basis function networks. A total of 20,000 artificial neural structures were trained to equalize both time series. For each problem, five best neural networks (with the highest performance and the smallest error) were retained. Artificial neural networks were capable of expressing the characteristics of both time series very accurately and equalize them. The performance of the network expressed by correlation coefficient achieves the lowest value of 0.94, which indicates a very high dependency of the variables. Thanks to this, it was possible to predict the future development of export and import between the Russian Federation and the People's Republic of China very efficiently. The results clearly show that both monitored time series are going to grow in the nearest future.

Economic sanctions have always been, and will undoubtedly continue to be, among the strongest "weapons" of international policy. The threat alone causes changes in financial markets; it affects the population behavior as well as the business sector. Research confirms

that the multilateral measures, such as the sanctions imposed on the Russian Federation in 2014, are significantly more effective, but even they may not have the expected effect. In the globally interconnected world, the best alternative is applied, and the trade gap can be compensated relatively quickly and efficiently by increasing balance of trade with other partners. The research results show that the so-called anti-Russian sanctions contributed to the development of Russian-Chinese trade relations, and we have been able to quantify them precisely, including seasonal fluctuations. The mutual trade of the two powers will grow. In addition, the new setting and strengthening of trade relations contains the dynamics of its own development, which confirms the assumption of further (even originally unplanned) strengthening of trade between countries that do not participate in, or benefit from, the sanctions. This fact has also been fully confirmed by the research. It is therefore clear that the creators of sanction measures must include these effects in their expected impacts and related changes as a part of their preparations and calculations.

To investigate the effects of sanctions, vector auto-regression models are frequently used. Despite a number of advantages, they require stationary time series, and even typically low maximum time lag.

Equalizing of the time series, mutual export and import of two countries using neural networks appeared to be a very efficient tool for evaluating the efficiency and impact of sanctions especially on the third parties. With the correct configuration, neural networks are able to capture the overall trend of the time series as well as seasonal fluctuations (local extreme of the time series). What is interesting is the time series lag, in which the advantage consisting in the possibility of own dynamics and learning when including a large volume of variables is reflected. It can be used also for solving the problems including longer maximum lag, where the results generated provide a strong basis for predicting further development.

Although artificial neural networks show great results in this specific case, it is necessary to reduce the limitations of the results or shortcomings of the application of artificial neural networks. As in almost all cases, the quality of the result is directly dependent on selecting the right variables and on the quality of the input data and their distribution into training, testing, and validation datasets. At the beginning, it is also very important to estimate possible time fluctuations. A problem when we deal with export and import reported monthly does not provide much space for error; however, if the variables were monitored every day, the fluctuation would be apparent within weeks and months. A shortcoming of the application of neural networks definitely includes possible overfitting of networks. In such a case, neural networks show excellent parameters of equalized time series; however, they predict nonsensical values. When this happens, it is necessary to verify the result obtained using heuristic methods. Finally, it has to be mentioned that the resulting model is a result of experiment. Even if the parameters of the model are set in the same way when repeating the algorithm of the model creation, the results will be almost certainly different in terms of their inner structure. However, they will also be successful (their performance and error). Nevertheless, if the model is fitted, it will provide the same result if the same combination of the input data is used.

Despite its shortcomings, the model is very accurate and successful; it can thus be stated that the objective of the paper was achieved. Another paper or study should deal with and reduce the limitations of the results.

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**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Publicly available datasets were analyzed in this study. This data can be found here: <https://data.imf.org/?sk=9D6028D4-F14A-464C-A2F2-59B2CD424B85>.

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**Conflicts of Interest:** The author declares no conflict of interest.

**Appendix A**

Appendix A.1. Export

Appendix A.1.1. 1-Month Time Series Lag

**Summary of Active Networks: Export**

Index	Net. Name	Training Perf.	Test Perf.	Validation Perf.	Training Error	Test Error	Validation Error	Training Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 13-5-1	0.964118	0.941782	0.965376	64,633.79	98,418.7	90,892.15	BFGS 94	SOS	Logistic	Tanh
2	MLP 13-6-1	0.962371	0.934458	0.962191	68,071.21	109,802.9	74,079.67	BFGS 36	SOS	Logistic	Logistic
3	MLP 13-4-1	0.971666	0.942705	0.96687	51,599.89	99,085.5	68,101.9	BFGS 61	SOS	Logistic	Exponential
4	MLP 13-7-1	0.981881	0.958261	0.976365	33,173.23	72,821.7	48,599.45	BFGS 133	SOS	Logistic	Exponential
5	MLP 13-4-1	0.97653	0.951515	0.978344	44,456.05	93,516.9	60,713.31	BFGS 83	SOS	Logistic	Tanh

Note: BFGS algorithm = Broyden–Fletcher–Goldfarb–Shanno algorithm; SOS = Safe Operation Stop function; Tanh function = hyperbolic tangent function.

**Predictions Statistics, Target: Export**

Statistics	1.MLP 13-5-1	2.MLP 13-6-1	3.MLP 13-4-1	4.MLP 13-7-1	5.MLP 13-4-1
Minimum prediction (Train)	-48.14	92.81	204.91	92.76	87.22
Maximum prediction (Train)	5703.67	5504.56	5285.57	4888.29	5786.67
Minimum prediction (Test)	16.49	116.52	205.20	92.76	180.41
Maximum prediction (Test)	5085.96	4594.78	5075.24	4888.22	5596.38
Minimum prediction (Validation)	-195.58	93.64	205.17	92.76	215.92
Maximum prediction (Validation)	5314.03	4706.45	4914.68	4888.29	5279.32
Minimum residual (Train)	-1409.63	-1278.85	-1121.77	-1042.61	-1043.81
Maximum residual (Train)	1105.42	1339.59	1127.94	1048.73	725.73
Minimum residual (Test)	-1182.00	-1063.78	-914.06	-896.18	-1448.43
Maximum residual (Test)	1116.97	1282.21	1289.08	1228.61	1320.54
Minimum residual (Validation)	-1447.06	-1408.09	-1087.19	-1031.41	-1038.28
Maximum residual (Validation)	615.20	877.11	764.88	641.54	574.97
Minimum standard residual (Train)	-5.54	-4.90	-4.94	-5.72	-4.95
Maximum standard residual (Train)	4.35	5.13	4.97	5.76	3.44
Minimum standard residual (Test)	-3.77	-3.21	-2.90	-3.32	-4.74
Maximum standard residual (Test)	3.56	3.87	4.10	4.55	4.32
Minimum standard residual (Validation)	-4.80	-5.17	-4.17	-4.68	-4.21
Maximum standard residual (Validation)	2.04	3.22	2.93	2.91	2.33

Appendix A.1.2. 3-Month Time Series Lag

Summary of Active Networks: Export

Index	Net. Name	Training Perf.	Test Perf.	Validation Perf.	Training Error	Test Error	Validation Error	Training Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 39-3-1	0.97532033	0.94195947	0.96247204	44,059.0306	97,526.5858	67,426.7124	BFGS 403	SOS	Logistic	Exponential
2	MLP 39-4-1	0.97357597	0.9452088	0.98021157	47,495.3908	94,752.6937	40,929.7788	BFGS 63	SOS	Logistic	Tanh
3	MLP 39-4-1	0.96949132	0.94504827	0.96890301	54,425.1995	94,208.2191	60,900.6634	BFGS 62	SOS	Logistic	Sine
4	MLP 39-4-1	0.97813455	0.94161045	0.96616922	39,075.6848	97,471.407	60,995.4233	BFGS 210	SOS	Logistic	Exponential
5	MLP 39-5-1	0.98254397	0.93703105	0.97883517	31,273.7412	105,188.295	46,845.2416	BFGS 130	SOS	Tanh	Logistic

Predictions Statistics, Target: Export

Statistics	1.MLP 39-3-1	2.MLP 39-4-1	3.MLP 39-4-1	4.MLP 39-4-1	5.MLP 39-5-1
Minimum prediction (Train)	284.66	134.96	54.53	216.58	224.25
Maximum prediction (Train)	4921.19	5653.00	5764.33	4911.88	5047.28
Minimum prediction (Test)	287.81	131.02	55.82	217.17	316.00
Maximum prediction (Test)	4883.37	5374.72	5204.20	4850.73	5001.04
Minimum prediction (Validation)	287.20	108.24	72.92	216.85	315.92
Maximum prediction (Validation)	4904.14	5008.12	5107.40	4906.46	4998.94
Minimum residual (Train)	-953.33	-924.71	-948.70	-934.85	-1036.51
Maximum residual (Train)	1115.98	801.98	1128.49	963.43	1087.54
Minimum residual (Test)	-862.53	-1282.22	-1118.09	-880.37	-1123.55
Maximum residual (Test)	1294.05	1451.70	1078.16	1320.29	1766.29
Minimum residual (Validation)	-1054.21	-875.06	-921.31	-1022.13	-1008.88
Maximum residual (Validation)	1287.41	567.66	619.39	1333.29	668.48
Minimum standard residual (Train)	-4.54	-4.24	-4.07	-4.73	-5.86
Maximum standard residual (Train)	5.32	3.68	4.84	4.87	6.15
Minimum standard residual (Test)	-2.76	-4.17	-3.64	-2.82	-3.46
Maximum standard residual (Test)	4.14	4.72	3.51	4.23	5.45
Minimum standard residual (Validation)	-4.06	-4.33	-3.73	-4.14	-4.66
Maximum standard residual (Validation)	4.96	2.81	2.51	5.40	3.09

Appendix A.1.3. 6-Month Time Series Lag

Summary of Active Networks: Export

Index	Net. Name	Training Perf.	Test Perf.	Validation Perf.	Training Error	Test Error	Validation Error	Training Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 78-3-1	0.97644692	0.95202612	0.98359434	41,858.6744	83,708.843	46,262.5535	BFGS 62	SOS	Logistic	Sine
2	MLP 78-3-1	0.97564053	0.9442971	0.96913162	43,239.5805	96,061.9557	57,371.2003	BFGS 182	SOS	Logistic	Exponential
3	MLP 78-3-1	0.97541954	0.94265005	0.96675215	43,610.1888	96,817.8135	57,072.2957	BFGS 141	SOS	Logistic	Exponential
4	MLP 78-4-1	0.97629068	0.94894962	0.98091908	42,169.8767	87,437.7493	45,852.2848	BFGS 91	SOS	Tanh	Tanh
5	MLP 78-4-1	0.97673919	0.94871987	0.98170221	41,307.2543	86,825.5632	41,116.7293	BFGS 100	SOS	Tanh	Tanh

Predictions Statistics, Target: Export

Statistics	1.MLP 78-3-1	2.MLP 78-3-1	3.MLP 78-3-1	4.MLP 78-4-1	5.MLP 78-4-1
Minimum prediction (Train)	297.90	207.16	262.14	159.52	172.26
Maximum prediction (Train)	5816.45	4950.51	4935.57	5644.4	5574.49
Minimum prediction (Test)	298.73	208.22	264.52	239.96	218.05
Maximum prediction (Test)	5405.34	4914.97	4898.08	5338.78	5261.11
Minimum prediction (Validation)	299.10	213.43	273.65	373.34	384.65
Maximum prediction (Validation)	5376.65	4924.78	4917.57	5271.58	5173.10
Minimum residual (Train)	-834.67	-964.01	-1022.59	-808.13	-759.34
Maximum residual (Train)	981.55	1119.31	1124.36	825.71	890.25
Minimum residual (Test)	-1197.71	-873.81	-860.74	-1138.27	-1031.82
Maximum residual (Test)	1198.67	1295.36	1305.34	1347.08	1359.34
Minimum residual (Validation)	-1001.30	-1051.11	-1049.21	-891.97	-806.97
Maximum residual (Validation)	401.8	847.69	849.64	470.37	477.99
Minimum standard residual (Train)	-4.08	-4.64	-4.90	-3.94	-3.74
Maximum standard residual (Train)	4.80	5.38	5.38	4.02	4.38
Minimum standard residual (Test)	-4.14	-2.82	-2.77	-3.85	-3.50
Maximum standard residual (Test)	4.14	4.18	4.20	4.56	4.61
Minimum standard residual (Validation)	-4.66	-4.39	-4.39	-4.17	-3.98
Maximum standard residual (Validation)	1.87	3.54	3.56	2.20	2.36

Appendix A.2. Import

Appendix A.2.1. 1-Month Time Series Lag

Summary of Active Networks: IMPORT

Index	Net. Name	Training Perf.	Test Perf.	Validation Perf.	Training Error	Test Error	Validation Error	Training Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 13-7-1	0.98211663	0.95546928	0.98489223	57,955.1319	139,584.498	46,306.5759	BFGS 167	SOS	Tanh	Identity
2	MLP 13-4-1	0.98273425	0.95747403	0.98434451	55,937.4497	128,193.356	48,507.2954	BFGS 169	SOS	Tanh	Identity
3	MLP 13-8-1	0.98412979	0.9581458	0.98526247	51,449.4647	131,787.876	49,657.3749	BFGS 116	SOS	Tanh	Identity
4	MLP 13-4-1	0.98211731	0.9515452	0.98393823	58,018.5351	152,635.45	50,054.0195	BFGS 109	SOS	Tanh	Identity
5	MLP 13-5-1	0.98559157	0.96022997	0.98312111	46,746.8031	121,708.496	57,921.0907	BFGS 197	SOS	Tanh	Identity

Predictions Statistics, Target: Import

Statistics	1.MLP 13-7-1	2.MLP 13-4-1	3.MLP 13-8-1	4.MLP 13-4-1	5.MLP 13-5-1
Minimum prediction (Train)	-283.72	-267.90	-14.83	101.94	38.51
Maximum prediction (Train)	5441.74	5290.27	5382.37	4989.72	5586.51
Minimum prediction (Test)	-66.12	-87.62	19.27	103.32	47.90
Maximum prediction (Test)	5002.03	4962.02	5215.37	4740.85	4883.06
Minimum prediction (Validation)	-104.23	-31.10	-4.29	102.26	51.10
Maximum prediction (Validation)	5057.82	5134.64	4988.22	4990.36	5050.67
Minimum residual (Train)	-1212.89	-1030.75	-1110.61	-1310.34	-1199.08
Maximum residual (Train)	1095.78	1184.97	1164.59	1095.67	1033.33
Minimum residual (Test)	-1677.56	-1538.15	-1679.91	-1734.11	-1813.82
Maximum residual (Test)	1267.85	1338.18	1328.27	1310.81	1110.90
Minimum residual (Validation)	-772.36	-740.95	-833.57	-836.22	-812.02
Maximum residual (Validation)	752.94	913.17	785.70	960.33	987.50
Minimum standard residual (Train)	-5.04	-4.36	-4.90	-5.44	-5.55
Maximum standard residual (Train)	4.55	5.01	5.13	4.55	4.78
Minimum standard residual (Test)	-4.49	-4.30	-4.63	-4.44	-5.20
Maximum standard residual (Test)	3.39	3.74	3.66	3.36	3.18
Minimum standard residual (Validation)	-3.59	-3.36	-3.74	-3.74	-3.37
Maximum standard residual (Validation)	3.50	4.15	3.53	4.29	4.10

Appendix A.2.2. 3-Month Time Series Lag

Summary of Active Networks: IMPORT

Index	Net. Name	Training Perf.	Test Perf.	Validation Perf.	Training Error	Test Error	Validation Error	Training Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 39-3-1	0.982084293	0.955739315	0.982493276	57,496.5482	142,352.549	58,376.4509	BFGS 79	SOS	Tanh	Sine
2	MLP 39-7-1	0.985733635	0.961027279	0.983817619	45,763.9348	120,769.779	58,875.8861	BFGS 159	SOS	Tanh	Sine
3	MLP 39-5-1	0.984727318	0.955798472	0.981888107	48,998.1328	135,649.617	55,682.3959	BFGS 93	SOS	Tanh	Identity
4	MLP 39-5-1	0.983538279	0.961110378	0.983026428	52,813.4803	125,365.301	58,710.492	BFGS 101	SOS	Tanh	Sine
5	MLP 39-4-1	0.980490573	0.945832085	0.981664831	62,563.002	173,455.585	56,615.7557	BFGS 104	SOS	Tanh	Sine

Predictions Statistics, Target: Import

Statistics	1.MLP 39-3-1	2.MLP 39-7-1	3.MLP 39-5-1	4.MLP 39-5-1	5.MLP 39-4-1
Minimum prediction (Train)	-42.02	-62.84	-25.60	-6.66	92.08
Maximum prediction (Train)	5077.02	5188.27	5475.82	5379.54	5384.16
Minimum prediction (Test)	-12.48	-64.68	10.49	4.68	92.12
Maximum prediction (Test)	4762.13	4968.92	4623.28	5160.24	4883.31
Minimum prediction (Validation)	-13.08	-57.71	-36.59	-42.16	91.66
Maximum prediction (Validation)	5026.38	5080.21	5142.23	4992.38	4915.67
Minimum residual (Train)	-1167.65	-1060.10	-1140.91	-1144.08	-1437.42
Maximum residual (Train)	1128.87	1192.25	1058.99	1091.53	1253.09
Minimum residual (Test)	-1701.33	-1673.42	-1669.27	-1686.41	-1914.78
Maximum residual (Test)	1125.09	1257.89	1232.87	1135.85	1115.67
Minimum residual (Validation)	-896.25	-934.75	-682.29	-910.03	-965.45
Maximum residual (Validation)	899.06	814.72	1094.66	848.94	940.96
Minimum standard residual (Train)	-4.87	-4.96	-5.15	-4.98	-5.75
Maximum standard residual (Train)	4.71	5.57	4.78	4.75	5.01
Minimum standard residual (Test)	-4.51	-4.82	-4.53	-4.76	-4.60
Maximum standard residual (Test)	2.98	3.62	3.35	3.21	2.68
Minimum standard residual (Validation)	-3.71	-3.85	-2.89	-3.76	-4.06
Maximum standard residual (Validation)	3.72	3.36	4.64	3.50	3.95

Appendix A.2.3. 6-Month Time Series Lag

Summary of Active Networks: Import

Index	Net. Name	Training Perf.	Test Perf.	Validation Perf.	Training Error	Test Error	Validation Error	Training Algorithm	Error Function	Hidden Activation	Output Activation
1	MLP 78-8-1	0.980660	0.947515	0.977350	61,538.73	166,992.1	65,690.75	BFGS 89	SOS	Tanh	Identity
2	MLP 78-4-1	0.982732	0.955443	0.981321	54,946.94	136,337.8	55,504.71	BFGS 102	SOS	Tanh	Identity
3	MLP 78-3-1	0.984100	0.955061	0.982016	50,601.03	139,823.6	59,876.39	BFGS 126	SOS	Logistic	Identity
4	MLP 78-5-1	0.980382	0.953199	0.976726	62,829.26	148,745.4	77,402.81	BFGS 146	SOS	Tanh	Logistic
5	MLP 78-5-1	0.985191	0.959920	0.982193	47,285.03	119,485.7	51,174.38	BFGS 154	SOS	Tanh	Exponential

Predictions Statistics, Target: Import

Statistics	1.MLP 78-8-1	2.MLP 78-4-1	3.MLP 78-3-1	4.MLP 78-5-1	5.MLP 78-5-1
Minimum prediction (Train)	-37.96	27.26	23.46	42.79	42.92
Maximum prediction (Train)	5557.44	5547.49	5702.71	5145.17	5602.16
Minimum prediction (Test)	0.06	28.20	28.53	42.79	42.99
Maximum prediction (Test)	5052.58	5104.16	5334.23	5002.21	5085.20
Minimum prediction (Validation)	-1.30	30.35	29.95	42.79	43.02
Maximum prediction (Validation)	4776.93	5126.97	5201.12	4549.86	4993.25
Minimum residual (Train)	-1367.68	-1066.21	-1290.16	-1537.74	-1167.61
Maximum residual (Train)	1124.21	1142.49	992.10	1079.38	982.56
Minimum residual (Test)	-1742.63	-1557.97	-1565.99	-1634.06	-1571.91
Maximum residual (Test)	1125.11	1296.51	1331.98	1342.31	1173.03
Minimum residual (Validation)	-1012.55	-702.37	-890.03	-784.47	-676.09
Maximum residual (Validation)	859.16	1000.17	957.20	1163.80	1007.69
Minimum standard residual (Train)	-5.51	-4.55	-5.74	-6.13	-5.37
Maximum standard residual (Train)	4.53	4.87	4.41	4.31	4.52
Minimum standard residual (Test)	-4.26	-4.22	-4.19	-4.24	-4.55
Maximum standard residual (Test)	2.75	3.51	3.56	3.48	3.39
Minimum standard residual (Validation)	-3.95	-2.98	-3.64	-2.82	-2.99
Maximum standard residual (Validation)	3.35	4.25	3.91	4.18	4.45



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