Artificial Neural Networks in Export and Import Forecasting: An Analysis of Opportunities

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***Abstract*–The paper concerns the issue of forecasting trends in trade relations between Malaysia and Ukraine using artificial neural networks. The current state of trade relations between the countries in the context of the COVID-19 pandemic has been analyzed. Considering the advantages and disadvantages of the types of neural networks built into the software product STATISTICA 10, MLP network has been chosen to build a predictive model of imports and exports of goods. The forecast values for the volumes of exports and imports of goods for the period from January 2021 to December 2022 have been calculated. Comparing the results, the researchers concluded that the artificial neural network is the most successful model for forecasting imports and exports. Suggestions for effective evaluation and forecasting of international trade indicators using the theory of time series and neural network technologies are given and the directions of further scientific research arising from this paper are formed.**

Keywords–export, import, forecasting, neural network, Malaysia, Ukraine

I. Introduction

A study of trade and economic cooperation between Malaysia and Ukraine indicated that an important aspect is to build effective forecasting models. Taking into account the nature of the trade process, time series theory is often used to study it. Choosing the right model is extremely important because it describes the major trends in trade relations between Malaysia and Ukraine and thanks to it get predictive values in the future.

The most popular model for forecasting time series is ARIMA. This model has a very clear mathematical and statistical justification, which makes it one of the most scientifically important among many other models for predicting trends in time series. The basis of the approach to the construction of the ARIMA model is based on the hypothesis of process stability.

Artificial neural networks are the alternative to time series prediction and have gained immense popularity over the past few years. The main task of neural networks is to build a model to simulate the intelligence of the human brain using a computer. Neural technologies try to recognize patterns in the input data, draw conclusions from the behavior of the model, and then provide generalized results based on their previous knowledge. Neural networks are self-adaptive, so there is no need to specify an exact model or make a priori assumptions about the statistical distribution of data; the forecast model is based on the characteristics presented on the basis of statistical data. Modeling using neural networks is more practical and accurate in data prediction, in contrast to traditional linear approaches such as ARIMA methods. In addition, they simulate a situation even when the input data is incorrect, incomplete or blurred. It is these advantages of using artificial intelligence technologies that have led to the choice of neural network technologies as a tool for modeling and forecasting key trade indicators between Malaysia and Ukraine.

II. Related Work

A review of related works is structured in the following areas: general issues of artificial neural networks, artificial neural networks in forecasting, artificial neural networks and their use in certain sectors of the economy and human activity, artificial neural networks in forecasting foreign economic turnover between countries.

Many authors have addressed the problem of forecasting in the economy. Scientific researches suggest that although statistical forecasting of economic series began in the mid-twentieth century, the breakthrough came with the publication of the study [3], where the authors integrated all knowledge about autoregression models and the moving average. Since then, a significant number of authors pay close attention to their application in scientific and applied research. Over time, the situation has changed and some authors have begun to point out the shortcomings of these models. In particular, researcher [5] saw that the use of ARIMA models in financial modeling is not correct, because sequences usually have conditional deviations instead of constants. Therefore, he proposed ARCH (Autoregressive conditional heteroskedasticity) models for financial modeling.

[7] notes that artificial neural networks (ANNs) are learning systems. The neural system can be trained to set input and output data related to a particular problem. If new data of the same problem is fed into the system, but not in the training set, ANN can use the studied data to predict the results without any specific programming related to the category of events involved. The scope of ANN has grown dramatically over the past few years. Thus, having only a very modest knowledge of the theory underlying ANN, it is possible to solve complex problems in the researcher's own field with the help of ANN.

Numerous studies [4, 15, 16] have shown that an artificial neural network can work more efficiently than standard statistical (econometric) models.

According to [18] neural networks are widely used in a number of different areas. The main advantages include, for example, their ability to work with large amounts of data, accuracy of results, etc. [17, 20] argue that other benefits of neural network methods for predicting key business indicators include the ability to learn and generalize. Neural network models can also be used to approximate high-precision functions [18].

The work [1] is devoted to the study of the application of artificial neural network (ANN) to develop models for predicting the intensity of carbon emissions. The authors selected parameters that play an important role in contributing to the intensity of emissions were selected as input variables. Input parameters are economic growth, energy consumption, scientific development, financial development, foreign direct investment, trade openness, industrialization and urbanization. After numerous repetitions, the optimal models for each country were selected on the basis of predefined criteria. The results of the tested models show that the predicted and actual values indicate approximately no errors along with higher coefficients of determination (R2). The ANN models presented in this study have been validated and reliable for predicting emissions growth with minor forecasting errors. The authors emphasize that models can serve as a tool for forecasting and assisting in decision-making on climate change policy.

The paper [2] explore three types of neural network approaches for predicting natural gas consumption: the simple artificial perceptron neural network (ANN), state-of-the-art long-term short-term memory (LSTM), and the proposed deep neural network (DNN). In this research work, the implementation of DNN is proposed, where variables related to social aspects are introduced as input data. A comparative analysis is performed between the proposed DNN, simple ANN and profitable LSTM, and the results offer a deeper understanding of the characteristics of Greek cities and the usual patterns of their inhabitants. The proposed implementation shows the effectiveness of forecasting daily values of energy consumption for up to four years. A real data set for natural gas forecasting was used to evaluate the proposed approach. There is a detailed discussion on the effectiveness of the implemented approaches, ANN and LSTM, which are characterized as particularly accurate and effective in the literature. It is proposed the DNN with the inclusion of qualitative variables that regulate human behavior.

The paper [19] focuses on ANN for being used in predicting higher values of bamboo biomass heating. The three ANN models are based on input from direct analysis, final analysis, combined direct and final analysis. The prediction accuracy of these models is analyzed by comparing with experimental data graphically and statistically.

[14] combine different models of the most modern artificial neural networks and introduce an alternative in the development of accurate forecasts of various financial factors. The accuracy of their technique gives the impression that it is comparable to standard models. Authors present a new approach in predicting economic time series, it is the use of artificial neural networks. They suggest using an artificial neural network such as RBF in the process of forecasting financial data. In addition to standard RBF, the authors are also testing their own new versions of this neural network in combination with other ML methods.

These models represent a new and improved version of the standard neural network. The authors add an evolutionary approach to ANN, and also combine the standard ANN weight adaptation algorithm with an uncontrolled clustering algorithm called K-means. Finally, all these methods are compared and contrasted with the standard (statistical) approach to real economic data to show the potential of using an artificial neural network to model economic variables.

Authors of [9] notes that artificial neural networks are becoming increasingly popular for statistical models, mainly due to increased computing power and technology capabilities. This paper introduces the use of artificial neural network regression models. The author investigates the problems of forecasting GDP growth. It is shown that the ANN model is able to give much more accurate forecasts of GDP growth than the corresponding linear model. In particular, ANN models very flexibly capture time trends.

In [12, 13] are indicated the possibilities of applying the forecast of the tax on imports of goods and suggests the use of artificial intelligence in further research.

Meanwhile, [8] also point to the possibility of forecasting the stock market using an artificial neural network.

The issue of export forecasting is given considerable attention in the work [10]. The authors compare traditional statistical methods in the form of regression analysis of time series and artificial neural networks, which are very important forecasting tools and become an integral part of modeling and forecasting a certain development of time series based on statistical data. The researchers point out that the best option for linear regression is a curve obtained by the method of least squares with negative exponential smoothing. From the point of view of the correlation coefficient, only neural networks are used.

The scientific work [11] evaluates the relative effectiveness of factor models in forecasting GDP growth using a large quarterly data set. Common factors are identified by estimating both static and dynamic principal components and are used to calculate pseudo-predictions outside the sample in a recursive scheme. These predicted factors are then compared with a standard basic one-factor autoregressive model. The forecasting results show that the forecast errors of the base model increase with the forecast horizon, but the forecast errors of the factor models remain relatively unchanged.

International trade is a more complex process than domestic trade. [17] argue that artificial neural networks or regression time series can be used to predict the development of imports.

In paper [24] authors proposed a method for using neural networks to model impacts on the parameters of complex projects for predicting the level of changes in the results of the project activity.

Researchers [6] note that international trade policy has recently drawn attention to restricting cross-border trade in essential goods. However, trade has a critical impact on employment and wages. Therefore, predicting the future structure of trade is a priority. Although traditional economic models aim to be reliable predictors, the authors point to the possibility that machine learning (ML) methods allow to make better prediction of information for policy making. This paper describes international trade transactions and related economic factors. Deployed ML models include: ARIMA, GBoosting, XGBoosting and LightGBM for forecasting future trade models and K-Means clustering countries according to some economic factors.

Unlike short-term and subjective (straightforward) forecasts and medium-term (aggregate) forecasts, ML methods provide a range of managed data and interpreted forecasts.

This is not an exclusive list of responses to calls that cause the use of ANN. But they also emphasize the importance of the chosen topic and its relevance.

Based on analysis above the objective of the paper is to study the possibilities of using artificial neural networks to predict foreign economic turnover between Malaysia and Ukraine. In addition, the study aims to predict the importance of imports and exports of Malaysia and Ukraine.

III. RESEARCH METHODOLOGY

To perform the main task of this study, we propose the following hypotheses-assumptions testing experimentally for a possible solution. First, there is a direct relationship between COVID-19 disease and gross domestic product and what is the trend of exports and imports in the relationship between Malaysia and Ukraine. Second, the possibility of using time series theory and artificial neural networks to predict exports and imports between Malaysia and Ukraine and what import and export values can be predicted.

In methodological terms, our thoughts are presented in the following sequence. First, we listed the common starting points of our arguments i.e. the preconditions and conditions of our vision. At the next stage, we made an attempt to present our views on this range of issues. In the final phase, we focused on a possible solution to the problem and tested the developed theoretical and methodological material to test the proposed hypotheses.

In the process of writing the paper we used a systematic approach as one of the main methods of scientific research.

It was presented the research problem, the need to test the hypotheses adopted in the study, the need to develop a model led to the division of the research process into specific stages and the choice of appropriate methods in each of them. At the initial stage, we used the following scientific methods: literature review and analysis, direct observation, documentary method. In the future, we used such research methods as time series theory. The collected quantitative and qualitative empirical data were processed using artificial neural networks in the STATISTICA package.

IV. RESULTS AND DISCUSSION

Let's check the assumptions. To determine the degree of economic development of the country it is used certain indicators, the most important of which is GDP. Let's consider the dynamics of Malaysia's GDP during 2010-2020 (Fig. 1).

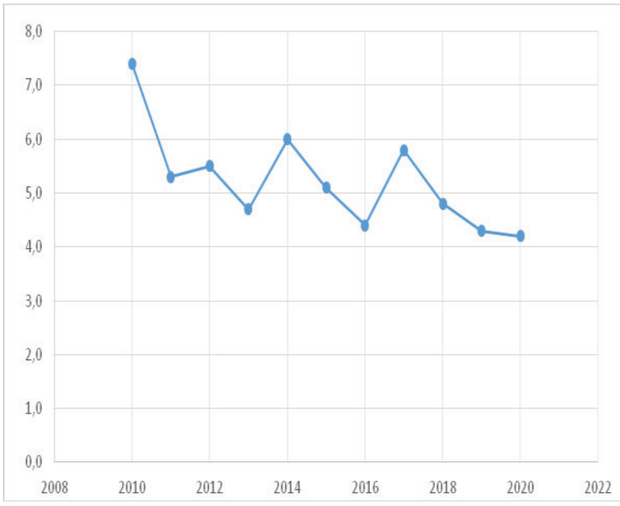

Figure 1. Dynamics of GDP in Malaysia

To achieve the goals set in the paper, we will also consider the dynamics of the incidence of COVID-19 in

Malaysia. For better visualization and comparison, we present it graphically.

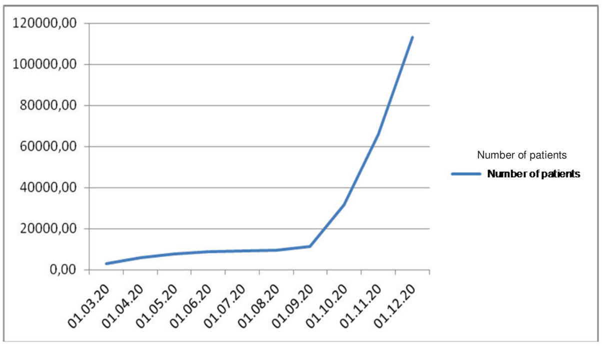

Figure 2. Dynamics of COVID-19 in Malaysia

In fig. 1 it is clearly shown that over the last three years there has been a decline in Malaysia's GDP. It is also known that GDP growth is closely linked to industrial production. In 2020, GDP was the lowest, i.e. production was reduced and consumption of goods and services was also the lowest.

However, we conclude that based on Figs. 2 it is not possible to say that the COVID-19 pandemic had a significant impact on economic growth, as in 2018-2019 the decline in GDP was more rapid. But for a better understanding, it is worth analyzing the indicators in 2021. Depending on the elasticity of demand for different goods and services, fluctuations in production in different industries occur differently.

Taking into consideration the COVID-19 pandemic, which has affected the world economy, a decline in key indicators is also observed in foreign trade. In this situation, special importance should be given to methods of forecasting import and export indicators, as the awareness of the decision-maker in the field of trade will allow to adjust the strategy of trade and economic cooperation with other countries to ensure stable development of the national economy.

Statistics[1] on the volume of exports and imports of goods in Malaysian ringgit for each month from January 2014 to December 2020 were used for modeling.

Let us first consider the trends in the dynamics of exports and imports of goods in trade relations between Malaysia and Ukraine during the study period (Fig. 3-4). According to the graphs, it can be determined that over a period of time the volume of exports and imports of goods increases, there is a growing linear trend and a certain frequency.

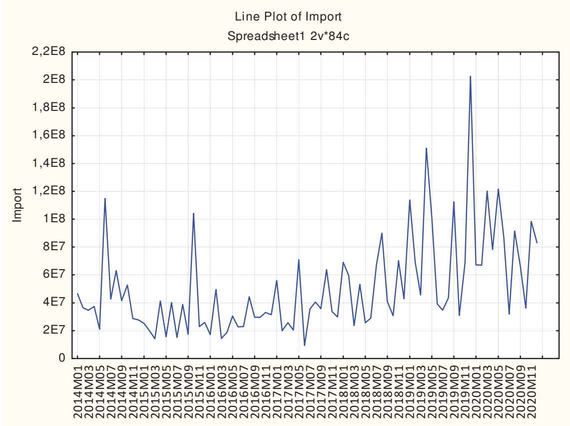

Figure 3. Line graph of imports of goods between Malaysia and Ukraine (January 2014-December 2020)

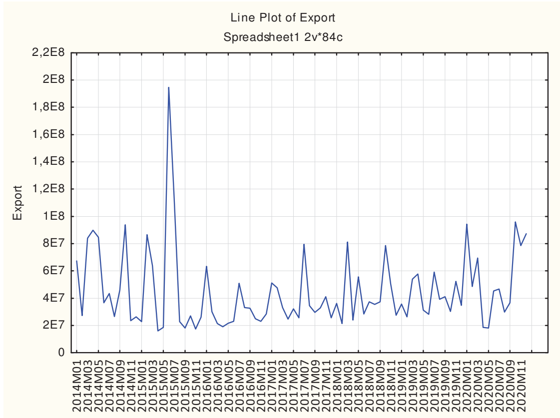

Figure 4. Line graph of exports of goods between Malaysia and Ukraine (January 2014-December 2020)

The STATICTICA 10 package includes a Neural networks module, which provides for the use of artificial intelligence technologies to build predictive models. This module offers two types of neural networks as prediction tools: MLP (multilayer perceptron) and RBF (radial-basis functions).

A network of the radial basis function (RBF) has an intermediate layer consisting of radial elements, each of which reproduces a Gaussian surface. Since these functions are nonlinear, it is not necessary to take more than one intermediate layer to model an arbitrary function, it is only necessary to take a sufficient number of radial elements. The RBF network has an output layer consisting of elements with linear activation functions.

Radial basis function (RBF) networks have a number of advantages over multilayer perceptron (MLP) networks. They simulate any nonlinear function using only one intermediate layer, and thus we do not need to decide how many layers the model will have. As well as the parameters of the linear combination in the source layer can be optimized using linear modeling methods that give a quick

[1]Compiled by the Statistical Data retrieved from https://trendeconomy.ru/

result and there are no difficulties with local minima, which is a disadvantage in MLP training. Therefore, the RBF network learns an order of magnitude faster than MLP.

However, to apply the methods of linear optimization in the source layer of the RBF network, it is necessary to determine the number of radial elements and the position of their centers and the magnitude of the deviations. These algorithms are less suitable for finding suboptimal solutions.

In addition, the differences between these two types of networks are related to the different representation of the model space: "group" in RBF and "planar" in MLP.

To obtain an adequate model using the RBF network requires more elements, considering its eccentric surface. Thus, the RBF-based model will run slower and require more memory than the corresponding MLP.

Since the RBF network has a "group" representation of space, as a result, it is unable to extrapolate its findings beyond the scope of known data and with the removal of some values from the training set, the function decreases to zero. For the MLP network, when processing deviant data, it gives more accurate predictive values.

Nowadays, MLP network architecture is used more often than RBF network. And the main reason is that the network of radial-basis functions (RBF) is too nonlinear and its training does not reduce the dimension, instead, when simulating with a multilayer perceptron network (MLP), each neuron has a limited field of perception and in each layer of them significantly decreases. The elements are organized in a layered topology with direct signal transmission and such a network can easily be interpreted as an "input-output" model, in which weights and thresholds are free parameters of the model.

The MLP network can simulate a function of any degree of complexity, in addition, the complexity of the function is determined by the number of layers and the number of elements in each layer. When training a multilayer perceptron (MLP) neural network, the number of layers and elements in each of them is first determined, and weights and thresholds are randomly assigned small initial values. As a result, they are virtually unrelated. In the process of learning the values of weights increase. Based on the values of weights and thresholds, the forecast error issued by the network is minimized.

Taking into account the advantages and disadvantages of two types of neural networks built into the software product STATISTICA 10, we chose the MLP network to build a forecast model of imports and exports of goods between Malaysia and Ukraine. To train the neural network, we use data from January 2014 to December 2019, and check the performance for the values of trade volumes during 2020. The adequacy of the models will be investigated by residue analysis. Thus, based on the results of the analysis (Figs. 5–6), 5 neural networks were obtained for the volumes of imports and exports, respectively.

Summary of active networks (Spreadsheet1)

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 36-3-1	0,541488	0,727118	0,689993	3,122748E+14	2,081923E+14	6,889233E+13	BFGS 5	SOS	Tanh	Logistic
2	MLP 36-4-1	0,519466	0,687895	0,684622	3,205913E+14	2,344020E+14	4,317437E+13	BFGS 5	SOS	Logistic	Tanh
3	MLP 36-6-1	0,793505	0,867127	0,700219	1,453259E+14	2,166041E+14	3,983113E+14	BFGS 13	SOS	Logistic	Identity
4	MLP 36-2-1	0,534108	0,726771	0,693617	3,139681E+14	2,170036E+14	3,757937E+13	BFGS 5	SOS	Exponential	Logistic
5	MLP 36-2-1	0,724449	0,876334	0,712568	2,000384E+14	1,939549E+14	1,803445E+14	BFGS 12	SOS	Logistic	Tanh

Figure 5. The results of modeling the volume of imports of goods between Malaysia and Ukraine

Summary of active networks (Spreadsheet1)

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 24-5-1	0,464757	0,161980	0,886869	1,258472E+14	2,055745E+14	7,606486E+13	BFGS 8	SOS	Identity	Exponential
2	MLP 24-6-1	0,683566	-0,089520	0,836452	7,566091E+13	2,696356E+14	9,690751E+13	BFGS 10	SOS	Identity	Exponential
3	MLP 24-3-1	0,437811	-0,006800	0,686677	9,830757E+13	1,645827E+14	1,464954E+14	BFGS 10	SOS	Logistic	Logistic
4	MLP 24-2-1	0,318471	0,465295	0,346263	1,191534E+14	1,495182E+14	1,549313E+14	BFGS 4	SOS	Exponential	Identity
5	MLP 24-2-1	0,348587	-0,318053	0,373263	1,173059E+14	1,771829E+14	1,528343E+14	BFGS 4	SOS	Identity	Exponential

Figure 6. The results of modeling the volume of exports of goods between Malaysia and Ukraine

From the five neural networks for import and export volumes, we choose the one that best describes the forecast series. This choice is made using graphs of predicted values of models (Fig. 6-7).

According to the graphs (Fig. 7-8), we see that the series obtained using the MLP 36-6-1 model is closest to the real statistics of import volumes, and for export volumes we choose the MLP 24-6-1 model.

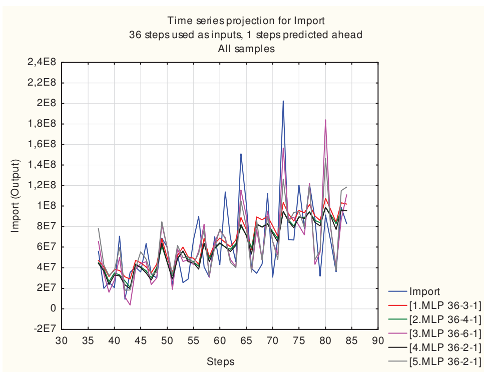

Figure 7. Graph of predicted values of neural network models for import of goods

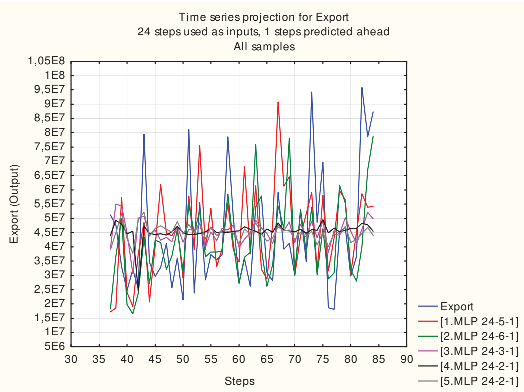

Figure 8. Graph of predicted values of neural network models for export of goods

Visual confirmation of the choice of selected models is shown on the graphs of the projection of time series (Fig. 9-10).

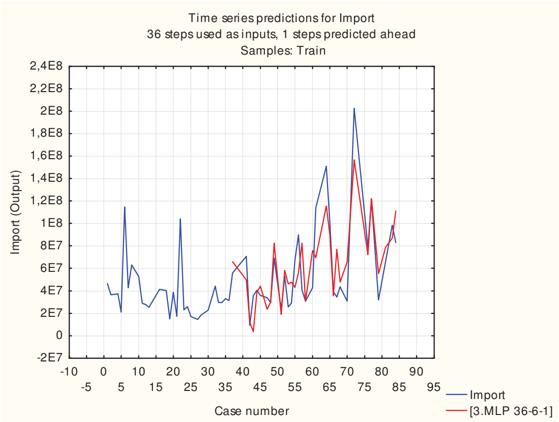

Figure 9. Projection of the time series of imports of goods

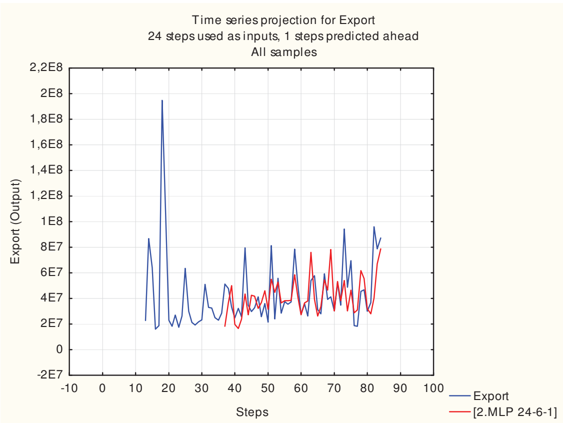

Figure 10. Projection of the time series of exports of goods

To confirm the correctness of the results obtained during modeling, we check the adequacy of the models based on the analysis of their residues. The condition for the adequacy of the models is the normal distribution of residues. To perform graphical analysis of model residues, we construct histograms for them (Fig. 11–12) and normal probability graphs (Fig. 13–14).

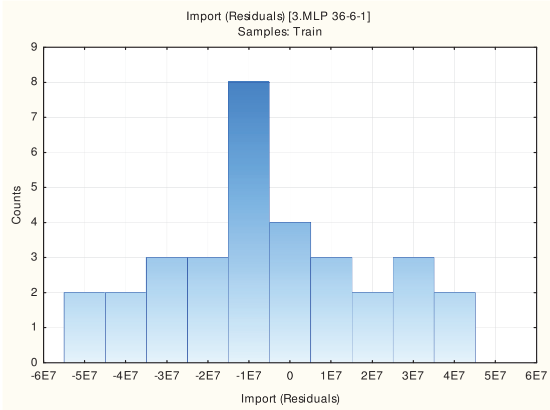

Figure 11. Histogram of the balances of the forecast model of import volumes

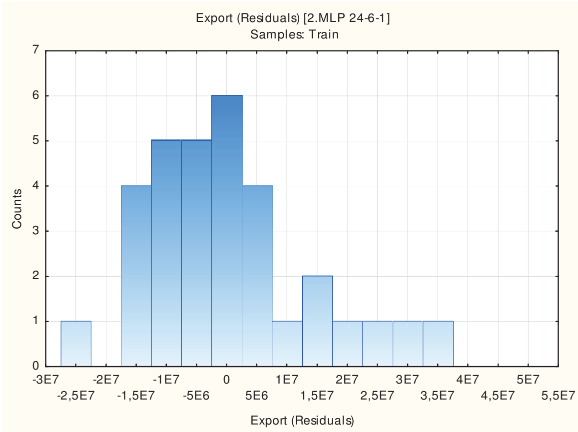

Figure 12. Histogram of the balances of the forecast model of export volumes

Thus, in Fig. 11–12 we see that the remainders of the two forecast models are distributed according to the normal distribution law.

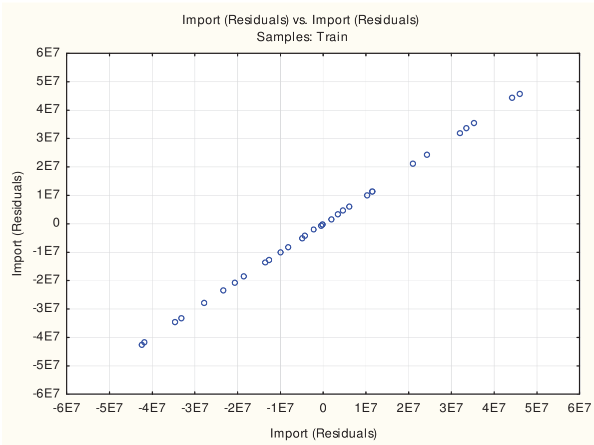

Figure 13. Normal probability graph of the balances of the forecast model of import volumes

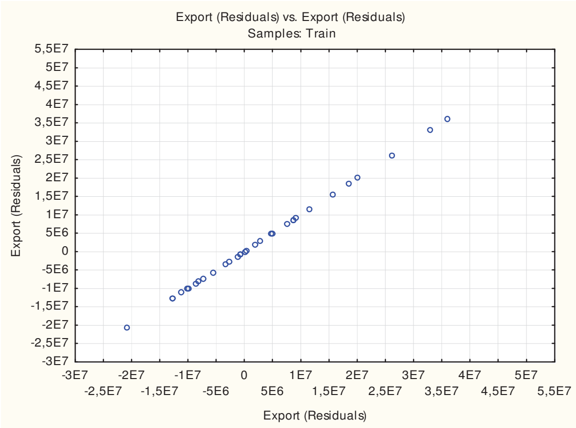

Figure 14. Normal probability graph of the balances of the forecast model of export volumes

Meanwhile, taking into consideration that the greater the approximation of the distribution to the normal value of the residues form a straight line, according to Figs. 13–14 determine that a number of model residues are normally distributed, so normal probability graphs are depicted as a linear relationship. On the basis of the conducted graphic analysis of the residues it is possible to state about sufficient adequacy of the constructed models.

After checking the constructed neural network models for adequacy, they can be used as a tool for forecasting the volume of exports and imports of trade flows between Malaysia and Ukraine for future periods.

We have evaluated the forecast values for the volume of exports and imports of goods between Malaysia and Ukraine for the period from January 2021 to December 2022. The data obtained are displayed graphically (Fig. 15-16) and presented in the table (Fig. 17-18).

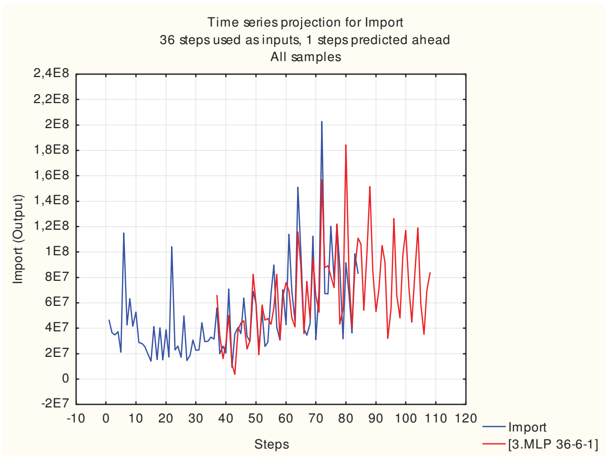

Figure 15. Graph of forecast values of imports of goods between Malaysia and Ukraine (January 2021-December 2022)

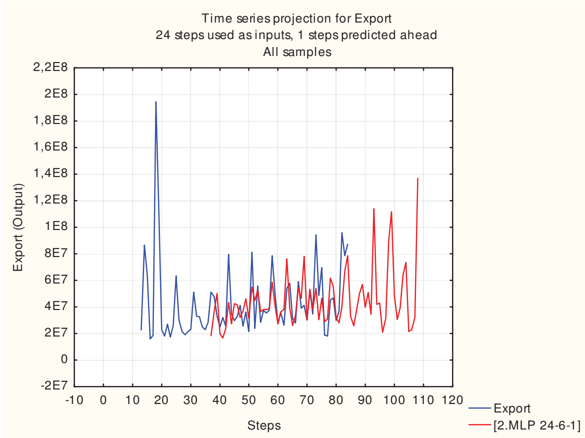

Figure 16. Graph of forecast values of exports of goods between Malaysia and Ukraine (January 2021-December 2022)

Case name	Time series projection for Import (Spreadsheet1) Import Target	Import(Output) MLP 36-6-1
2021M01		106020823
2021M02		54108043
2021M03		100922399
2021M04		151489290
2021M05		85075888
2021M06		53089254
2021M07		70436301
2021M08		105109758
2021M09		91932702
2021M10		32061399
2021M11		55425624
2021M12		126176181
2022M01		65733205
2022M02		48177872
2022M03		97804719
2022M04		116929309
2022M05		71537849
2022M06		44729300
2022M07		85180127
2022M08		118893297
2022M09		59312664
2022M10		35125035
2022M11		69871101
2022M12		83564255

Figure 17. Forecast values of imports of goods between Malaysia and Ukraine (January 2021-December 2022)

Case name	Time series projection for Export (Spreadsheet1) Export Target	Export(Output) MLP 24-6-1
2021M01		32933608
2021M02		25903046
2021M03		37768932
2021M04		50082190
2021M05		56857656
2021M06		39695391
2021M07		50770012
2021M08		34355009
2021M09		114030436
2021M10		42063407
2021M11		42899919
2021M12		20955530
2022M01		31424642
2022M02		89240750
2022M03		111579101
2022M04		48423827
2022M05		30698564
2022M06		39373809
2022M07		64181163
2022M08		73421402
2022M09		21589841
2022M10		22880132
2022M11		32057404
2022M12		136971455

Figure 18. Forecast values of exports of goods between Malaysia and Ukraine (January 2021-December 2022)

V. Conclusions

Thus, on the basis of statistical data on imports and exports of goods between Malaysia and Ukraine for previous periods, using neural network technologies, we obtained forecast values of these indicators of trade cooperation for future periods. We have not established a direct relationship between COVID-19 disease and gross domestic product. Meanwhile, based on the study, we conclude that time series theory and neural network technologies can be used to assess and forecast international trade indicators effectively. The principle of neural network technology is the ability to learn from certain examples. Moreover, the neural network is able to change its behavior depending on changes in external factors and, considering the hidden patterns of a large set of data.

In our opinion, the study made it possible to form a basis for the further research: the use of blockchain technologies and artificial intelligence in conditions of uncertainty.

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