Predicting Future GDP Development by Means of Artificial Intelligence

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Abstract

GDP measures the monetary value of the total production of goods and services in a given country over a certain period of time. GDP establishes the economic performance of a country or region and is useful for comparing differences in the living standards of nations. In general, three methods exist for determining GDP, based on production, expenditure and income. In today's modern world, economists are looking for other appropriate and improved models for the management and prediction of all economic indicators. Artificial intelligence is among those methods that have gained in importance because of its very good predictive ability over conventional statistical and mathematical models. It consists of a time series, for example, but especially of artificial neural networks. This paper describes the known applications of artificial intelligence for the prediction of GDP and then applies neural networks to predict the GDP growth of Eurozone countries until the year 2025. The selected neural structures exhibit satisfactory numerical characteristics and are equivalent to expert evaluations of GDP development. They therefore appear to be a useful tool for predicting GDP.

Keywords: GDP, Artificial Intelligence, Artificial Neural Network, prediction, Eurozone

Introduction

Gross Domestic Product (GDP) is defined by the OECD (2001) as ‘an aggregate measure of production equal to the sum of the gross values added of all resident and institutional units engaged in production (plus any taxes, and minus any subsidies, on products not included in the value of their outputs)’. It measures the monetary value of the aggregate production of goods and services in a country during a given time period (quarterly or yearly). Nominal GDP estimates make it possible to determine the economic performance of a whole country or region, and to make international comparisons.

However, it does not reflect differences in the cost of living and the inflation rates of the countries; therefore using gross domestic product (at purchasing power parity) (GDP PPP) on a per capita basis is arguably more useful when comparing differences in living standards between nations.

The structure of the GDP indicator

There are three ways of determining a nation's GDP, all of which should, in principle, give the same results. The most direct way is the product approach, which is the sum total of the outputs of every class of enterprise. The expenditure approach works on the principle that all of the product must be bought by someone, therefore the value of the total product must be equal to total expenditures. The income approach works on the principle that the incomes of the productive factors must be equal to the value of their product, whereby GDP is determined by finding the sum of the incomes of all producers.

Under the expenditure method, GDP (Y) is calculated according to (1):

$$Y = C + I + G + (C - M) \tag{1}$$

where C stands for consumption, I is investment, G stands for government spending, and X and M represent imports and exports respectively.

Artificial intelligence in forecasting

Artificial intelligence denotes a flexible and rational machine or piece of computer software that is able to change its actions in order to maximize its chance of success. Machines and programmes have become increasingly capable of solving extremely complex problems and situations and are able to help people in decision making, including sorting and assessing large amounts of data.

Central areas of artificial intelligence include reasoning, knowledge, planning, learning, natural language processing, perception and the ability to move and manipulate objects. Central approaches include statistical methods, computational intelligence, soft computing and traditional symbolic artificial intelligence. Planning includes prediction because without the ability to reasonably predict the future status quo, no effective planning can be made. Planning principally includes a periodical ascertainment as to whether the situation has changed to such an extent that it requires a change of plan or not.

Neural networks

Artificial Neural Networks are computation models inspired by biological neural networks, more precisely by the behaviour of neurons. They basically approximate functions that exist in model populations and environments that constantly change. Artificial Neural Networks are able to offer solutions to very complex models enhanced by artificial intelligence principles (Kliešťik 2013).

In various areas of business, artificial intelligence has been applied to help forecast diverse conditions. Various approaches and mathematical and statistical solutions have been used to ascertain comparability and evaluate mathematical aspects of the indicators of economic analyses (Vojteková and Bartošová 2009; Gazdíková and Šusteková 2009). Neural networks have, not unexpectedly, been compared to classical statistical methods and, in most literature, were found to perform better (Zhang, Cao and Schniederjans 2004; Kourentzes et al. 2013; Arunraj and Ahrens 2015; Mitrea, Lee and Wu 2009).

The economic and business predictive methods that were based on artificial neural networks were found to perform far better than classical statistical methods, although at times, they were accompanied by certain negative aspects and usually required extensive computation time or expert programming experience. The progress made in neural network development has brought with it more efficient models that can be more readily used in practice. The approach is to combine the neural networks with other methods to enhance speed or achieve more precise results. Various hybrid networks or combinations of neural networks and other methods have been developed in order to improve the performance of standard models. In other cases, neural networks were used along with various data pre-processing and sorting methods (Lahmiri 2016) or, in contrast, the data provided by neural network models were post-processed (e.g. Tsai and Chiou 2009, who used data predicted by a neural network model to construct a decision tree model to generate useful decision rules). The double clustering version (Specht 2006) is another example worthy of mention. According to Specht, the second clustering not only speeds up the testing, but also replaces the division required for kernel regression with simply the search for the nearest neighbour. The proper application of the neural model also depends on the character of the data - neural networks are especially suitable for long-term predictions with nonlinearities. Neural networks also offer an alternative way to deal with nonlinearity. Höglund (2012) compared two models based on traditional statistical approaches and three models based on neural networks (self-organizing map, multilayer perceptron and GRNN) and found that the GRNN model performed best, followed by the other two neural network models.

Time series

Time series are an ordered sequence of values of a variable at equally spaced time intervals (Lobos and Szewczyk 2014). Time series are used in many applications, such as economic forecasting. Time series analysis accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation).

Time series processes are often described by multiple linear regression (MLR) models (2):

$$y_t = X_t\beta + e_t \tag{2}$$

where y_t is an observed response and X_t includes columns for contemporaneous values of observable predictors. β are the partial regression coefficients that represent the marginal contributions of individual predictors to the variation in y_t when all of the other predictors are fixed. e_t is universal for differences between predicted and observed values of y_t due to process fluctuations in β, measurement errors in X_t, and model misspecifications.

Curak, Klime and Curak (2009) researched methods for forecasting economic growth using financial variables and compared linear regression and neural network models with regards to their ability to predict GDP growth. In the long-term, since nonlinearities could exist in the relationship between the variables, neural networks improve forecasting accuracy. Neural network models outperform linear regression models in forecasting accuracy. However, they suggest that in forecasting a macroeconomic variable such as GDP growth, in order to achieve better forecasting performances, both the linear regression and the neural network models can be combined.

The effects of disaggregation on forecasting non-stationary time series were tested by Poncela and García-Ferrer (2014). Using dynamic factor models, they compared the forecasts obtained directly from the aggregated series based on its univariate model with the aggregation of the forecasts obtained for each component of the aggregate. The results were then applied to the quarterly gross domestic product (GDP) data of several European countries in the Eurozone and to their aggregated GDP. The results were subsequently compared to the prediction obtained directly from the modelling and forecasting. Overall, the findings showed evidence that the factor model outperformed the remaining forecasts, probably due to its better behaviour at the turning points.

Predicting GDP

To determine whether the downturn in GDP of the USA was predictable, Balcilar, et al. (2015) used a small set of variables - real GDP, the inflation rate and the short-term interest rate – but a rich set of models – atheoretical and theoretical models (structural and time series), linear and nonlinear, and classical and Bayesian. After testing the models on limited data, they used the best model within each category to generate ex ante out-of-sample predictions of the real GDP. The findings showed that the nonlinear dynamic stochastic general equilibrium model (DSGE) performed the best overall for the ex post out-of-sample RMSE averaged across all horizons, as well as in tracking the turning point in the Great Recession, using ex ante out-of-sample predictions. This occurred despite the limited economic structure considered in Pichler's (2008) model, which introduces misspecifications. In other words, although our DSGE model entered the forecasting horserace at a disadvantage, it outperformed the 'atheoretical' time series models.

Saman (2011) modelled various scenarios of the Romanian GDP development with neural models. He strived to determine the nonlinear relation between investments and GDP and proposed two nonlinear models of GDP in relation to domestic investments, direct foreign investments and the real interest rate. The models were based on the kinds of neural network models already used for the prediction of macroeconomic variables, but he further enhanced them to be more accurate in a crisis situation characterized by structural breaks in data. A structural break that appears in linear models is a special form of nonlinearity that the neural net can learn. Both of the models presented good performance measures on the dataset, especially the long-term model.

Similarly, Tkacz (2001) applied neural networks to the forecasting of Canadian GDP growth with the same goal – to improve the accuracy of financial and monetary forecasts of Canadian output growth by using leading indicator neural network models. Although he found that neural networks yield statistically lower forecast errors for the year-on-year growth rate of real GDP relative to linear and univariate models, he claims that the forecast improvements are less notable when forecasting quarterly real GDP growth and that neural networks are unable to outperform a naive no-change model. He asserts that neural networks offer little value for short-term forecasts of GDP growth, whereas they perform noticeably better in long-term forecasts. Forecasters of macroeconomic variables could therefore achieve greater degrees of success if they focused on long-term forecasts.

Kiani (2016) employs eighteen USA macroeconomic time series variables to investigate the possible existence of asymmetries in business cycle fluctuations in the series. The study findings show statistically significant evidence of asymmetries in all the series which indicates that business cycle fluctuations in the series are indeed asymmetric. The results of the asymmetric business cycle fluctuations in real GDP are in line with other recent studies. In another study, Kiani (2010), uses neural networks to predict fluctuations in economic activity in selected members of the Commonwealth of Independent States using macroeconomic time series modelled recursively 1-10 quarters ahead and out-of-sample using a flexible ANN in conjunction with macroeconomic time series, so that all the countries achieve greater accuracy.

Ao and Tang (2007) published research on forecasts and analysis of the (1979-2003) GDP growth rate through chaotic time series forecasting methods. They performed a simulation forecast of the increasing rate and used back propagation neural networks as a method to predict the fitting errors of chaotic time series that didn't fit the actual fluctuation of small sample discrete data very well, which was especially true for long-term economic forecast errors. With their method, forecasting precision was greatly enhanced compared with only chaos forecasting and nonlinear regression methods.

On the basis of the Turkish economy, İnsel, Sualp and Karakas (2010) ran a detailed econometric and comparative analysis of the ARMA and neural network of the changes in real gross domestic product, among other economic indicators, based on monthly data. The results indicate that, when evaluated for their forecast performances, the neural network and ARMA models differ considerably depending upon the movements in the variables and the length of the sample period. Overall the predictive performance of both models was identical.

Sinclair, Stekler and Kitzinger (2010) applied the directional forecast approach to real GDP and inflation and undertook separate analyses of the Fed's forecasts. Their comparative method only applied to qualitative directional predictions since it considered a limited amount of information, the direction of change. They concluded that though some of the inflation forecasts, examined separately, were not valuable, the joint pattern of GDP and inflation projections was generally in accord with the economy's movements. Finally, we must note that this is a procedure for evaluating GDP growth and inflation forecasts.

The accuracy of macroeconomic forecasts can also be assessed at a regional level. Furthermore, regional indicators play a crucial role for forecasting regional GDP. Lehmann et al. (2013) strived to overcome the problem of a 'data-poor environment' at the sub-national level by complementing various regional indicators with more than 200 national and international indicators. They calculated single-indicator, multi-indicator, pooled and factor forecasts in a 'pseudo-real-time' setting. The results showed that forecast accuracy was significantly increased if compared with an autoregressive benchmark model, both for short-term and long-term predictions.

The forecasting of a business cycle with chaotic time series based on a neural network with weighted fuzzy membership functions was researched by Chai and Lim (2016). They presented a forecasting model for cyclical fluctuations in the economy based on the time delay coordinate embedding method. A comparative study was conducted using other methods based on wavelet transform and Principal Component Analysis for the performance comparison. The results were tested using a linear regression analysis to compare the approximation of the input data against the target class (GDP). Unlike the other two models, the chaos based model captured the nonlinear dynamics and interactions within the system and significantly improved the prediction capability - it demonstrated a far better approximation between the forecasted trends and the target class GDP, thereby identifying it as an excellent predictor of predominantly economic situations.

The aim of this article is to predict, with the help of neural networks, the development of the GDP of Eurozone countries until the year 2025.

Materials and Methods

Information on the development of the GDP of Eurozone countries is available on the server of the World Bank (2016). Specifically, data for the years 1960 to 2015 were used. The information is presented in millions of US dollars.

It was necessary to search for the time series of GDP growth in the reference period and, based on the results, to estimate the GDP growth of Eurozone countries until the year 2025. The prediction is therefore for the next ten years.

There were 56 rows of data available. MS Excel was used for the preparation of the data file. DELL Statistics software, versions 7 and 12, were used for the calculation. This was subsequently processed by automated neural networks.

All the used quantities were continuous. A module of time series created by regression was used. The data was divided into three groups:

- Training: 70%
- Testing: 15%
- Validating: 15%

The seed for random selection was set to a value of 1000. Subsampling took place randomly.

1000 artificial neural structures were subsequently generated, of which the 5 most appropriate were retained[1].

The following types of neural networks were used:

1. Neural network of the radial basic function (hereinafter also referred to as RBF);
2. Multiple perceptron of neural network (hereinafter also referred to as MLP).

The following was used as the activation function for the hidden and output layers:

1. Regression output encoding:
   a. Linear function:

$$y = k * x * w \tag{3}$$

where: y means output, k is transmitting function, x input, w synaptic weight.

   b. Step function:

$$S(t) = \begin{cases} 1 & ; \quad t \geq 0 \\ 0 & ; \quad t < 0 \end{cases} \tag{4}$$

where: t means time.

   c. Saturating linear function:

$$S(t) = \begin{cases} 1 & ; \quad t > 1 \\ t & ; \quad -1 \leq t \leq 1 \\ -1 & ; \quad t < -1 \end{cases} \tag{5}$$

   d. Sigmoid function:

$$S(t) = \frac{1}{1 + e^{-t}} \tag{6}$$

   e. Hyperbolic tangent function:

$$S(t) = \frac{1 - e^{-t}}{1 + e^{-1}} \tag{7}$$

A maximum of 11 neurons were used in the hidden layer of the RBF. A maximum of 20 neurons were used in the three-layer perceptron neural network.

Other settings were set as default.

[1] This is determined using the method of least squares. When differences between newly generated networks stop being substantial, training will be terminated.

Results and Discussion

The data was divided into three sets - training, testing and validating. The selection process was conducted randomly. Table 1 contains the basic data statistics of all three sets and simultaneously the compiled statistics of the entire series.

Table 1: Basic description statistics of the observed data set

Samples	Data statistics(GDP_euro)	
	Year	GDP
Minimum (Training)	1960.000	245,386
Maximum (Training)	2015.000	14,113,386
Mean (Training)	1988.825	5,834,212
Standard deviation(Training)	17.023	4,745,143
Minimum (Testing)	1965.000	408,114
Maximum (Testing)	2012.000	12,634,445
Mean (Testing)	1984.875	4,344,530
Standard deviation(Testing)	17.618	4,354672
Minimum (Validating)	1967.000	483,435
Maximum (Validating)	2003.000	8,850,018
Mean (Validating)	1983.500	3,465,192
Standard deviation (Validating)	21.521	3,323,065
Minimum (missing)		
Maximum (missing)		
Mean (missing)		
Standard deviation (missing)		
Minimum (Overall)	1960.000	245,386
Maximum (Overall)	2015.000	14,113,386
Mean (Overall)	1987.500	5,282,969
Standard deviation (Overall)	16.310	4,497,609

Source: Author

1000 neural networks were generated on the basis of the data sets. The five networks with the best statistics were retained. An overview of the obtained and preserved neural networks is given in Table 2.

Table 2: Overview of generated and preserved neural networks

Overview of active networks (GDP_euro)											
In	Networks name	Train. perform.	Test. perform.	Valid. perform.	Training error	Testing error	Valid. error	Train. Algorit.	Error function	Act. hidd. layer	Output act. fun.
1	RBF 1-10-1	0.995070	0.997693	0.998798	9.410417E+10	8.253469E+10	2.982181E+10	RBFT	Sum of sq.	Gauss	Identity
2	RBF 1-12-1	0.992732	0.991593	0.998530	1.433152E+11	2.161152E+11	2.769664E+10	RBFT	Sum of sq.	Gauss	Identity
3	RBF 1-11-1	0.994419	0.990489	0.999191	1.078230E+11	1.891966E+11	1.337156E+10	RBFT	Sum of sq.	Gauss	Identity
4	RBF 1-11-1	0.993065	0.992708	0.999446	1.363225E+11	1.985018E+11	2.274212E+10	RBFT	Sum of sq.	Gauss	Identity
5	RBF 1-13-1	0.993868	0.986834	0.998600	1.194787E+11	3.213900E+11	3.197014E+10	RBFT	Sum of sq.	Gauss	Identity

Source: Author

It is interesting that all the preserved neural networks are based on the radial basic function. It is clear from the table that all demonstrate excellent characteristics, as far as performance and error are concerned, in all three data sets. All five networks use the Gaussian curve as their activation function in the hidden layer, and identify the same function in their output layer. At first glance, it is therefore possible to generalize and state that the RBF is suitable for generating time series using regression.

Table 3 contains an analysis of the correlation coefficients of all the generated and preserved networks divided into training, testing and validating data series.

Table 3: Correlation coefficients of the individual data series

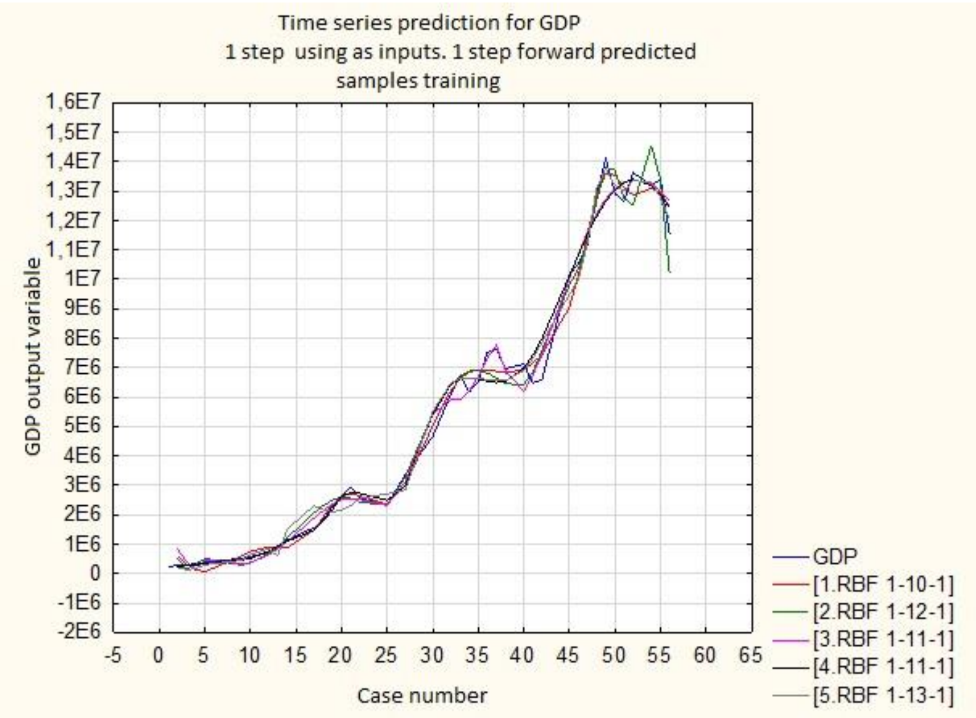
	Correlation coefficients (GDP_euro)		
	GDP	GDP	GDP
1.RBF 1-10-1	0.995070	0.997693	0.998798
2.RBF 1-12-1	0.992732	0.991593	0.998530
3.RBF 1-11-1	0.994419	0.990489	0.999191
4.RBF 1-11-1	0.993065	0.992708	0.999446
5.RBF 1-13-1	0.993868	0.986834	0.998600

Source: Author

From the given information it can be concluded that a very strong correlation exists in all five cases. The values of all data sets have values higher than 0.99.

On this basis, it is possible to compare each network with the actual performance of the economies of the Eurozone countries. The comparison is presented graphically in Figure 1 below.

Figure 1: Development of GDP, real and as predicted by neural structures



Note 1: The numbers of cases highlight each year, whereby the number 1 represents the year 1960 and 56 the year 2015.

Note 2: To compile the graph, only the training data set was used i.e. the one on the basis of which the model was created.
Source: Author

At first glance it can be claimed that all the networks faithfully copy the development of real GDP. It was therefore necessary to analyse residues in order to specify which of the networks was the most exact.

For this purpose, a sum of the residues was made:

1. RBF 1-10-1: - USD 2 million
2. RBF 1-12-1: - USD 136,044 million
3. RBF 1-11-1: - USD 1 million
4. RBF 1-11-1: - USD 113,563 million
5. RBF 1-13-1: - USD 213,182 million

It goes without saying, that a simple sum without the comparison of residues from the individual years may distort the result. However, it provides the first information on the value of the prediction of the individual networks. Ideally the sum of the residues should approach the value 0. From the obtained result, it was possible to conclude that the best result was achieved by network number 3, which was followed closely by network number 1.

On the basis of the defined individual models it was possible to continue onto the second part of the study, namely the prediction of the future development of the GDP of Eurozone countries for the years 2016 to 2025.

The results of the prediction are given in Table 4.

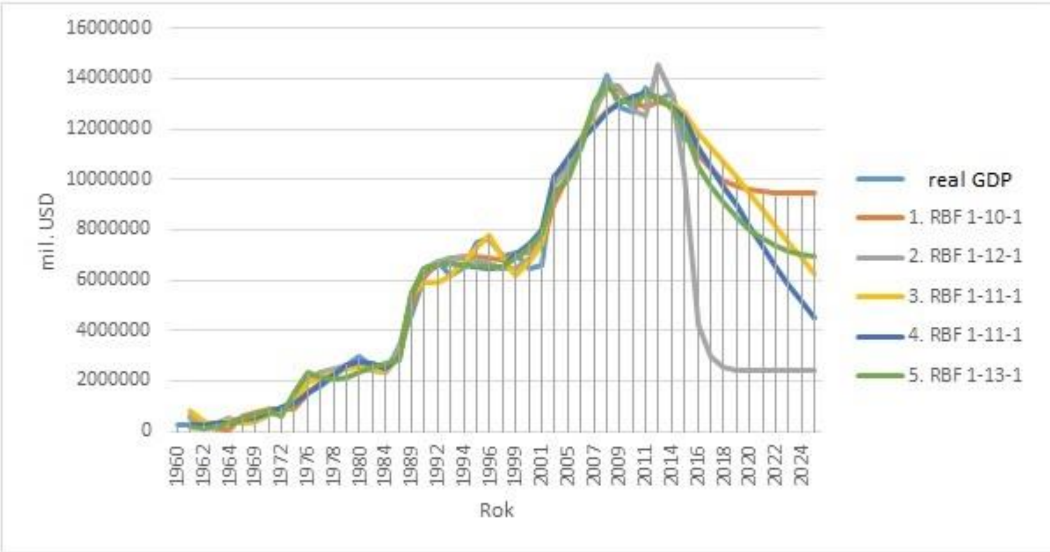
Table 4: Prediction of the development of GDP in Eurozone countries between 2016 to 2025

Cases	Table with user predictions (GDP_euro)					
	1.GDP_(t)	2.GDP_(t)	3.GDP_(t)	4.GDP_(t)	5.GDP_(t)	Year_(t-1)
1	11,013,754	4,224,724	11,798,496	11,235,908	10,491,802	2016.000
2	10,402,862	2,999,311	11,265,609	10,515,368	9,759,768	2017.000
3	9,971,310	2,550,408	10,685,157	9,742,087	9,092,758	2018.000
4	9,707,705	2,425,570	10,069,328	8,937,703	8,507,094	2019.000
5	9,566,949	2,398,247	9,430,340	8,123,308	8,017,747	2020.000
6	9,500,830	2,393,028	8,780,070	7,318,568	7,633,060	2021.000
7	9,473,396	2,391,850	8,129,717	6,540,968	7,350,520	2022.000
8	9,463,313	2,391,413	7,489,510	5,805,220	7,157,252	2023.000
9	9,460,024	2,391,192	6,868,474	5,122,876	7,034,218	2024.000
10	9,459,070	2,391,072	6,274,268	4,502,155	6,961,294	2025.000

Source: Author

Figures 2 is a graphical comparison of the predicted period and the previous period.

Figure 2: Development of GDP of Eurozone countries between 1961 and 2025



Source: Author

It is clear from the graph that an enormous drop in the GDP of Eurozone countries is predicted for the future period. On the basis of recent economic developments, mainly in the last few years, it is possible to conclude that a drop can be expected. In the case of the second, third and fourth networks, it is possible to talk more about a fall rather than a drop. In the case of the fifth network, the drop in GDP is also considerable, however, the model assumes it will bottom out and stabilize around the year 2023. The first RBF also assumes a large decline in GDP, but assumes that the developments surrounding the observed macroeconomic indicator will begin to stabilize in 2017.

On the basis of the residue analysis and conducted prediction of future development, it can be said with certainty that the most satisfactory results were generated by the first neural network, specifically RBF 1-10-1.

Conclusion

The aim of this paper was to predict the development of GDP of Eurozone countries until the year 2025.

Firstly, models of neural structures were generated and retained. It is of interest that all the preserved networks exhibited similar characteristics - not only where performance is concerned, but also their specification (type of neural structure, initiation function, error, etc.). On the basis of the conducted analysis, the RBF 1-10-1 network was determined to be the best. Not only did it exhibit satisfactory numerical characteristics - minimal residues, but it came substantially close to expert analysis of the possible development of GDP. The results of the analysis were the selection of the best artificial neural network and the prediction of GDP development of Eurozone countries.

The aim of this article was therefore fulfilled. The truth is, however, that the chosen prediction period of 10 years is very long. Despite making estimates for aggregated quantities, thereby minimising errors, it would have been highly appropriate to focus attention on the individual countries of the Eurozone, or eventually the individual fractional variables. This would have, with high probability, provided even better results.

In light of the obtained results, it can be stated that the RBF models appears to be the most useful tool for predicting GDP.

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