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PREDICTIVE ANALYSIS AND EVALUATION OF THE BULGARIAN ECONOMY'S MOST SIGNIFICANT INDICATORS

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Abstract: *This paper develops a mathematical algorithm to study and predict the future values of some of the Bulgarian economy's indicators. The considered exponents include the total exports & imports, the harmonized index of consumer prices, the total business climate indicator, the government balance – deficit / surplus and the long-term interest rate for convergence assessment purposes. The employed approaches for predictive analysis are the (S)ARIMA methods from the time-series toolkit and the NAR neural networks. The data is gathered from the Bulgarian National Bank and the National Statistical Institute. The aforementioned models are calibrated and forecasts are made, which, in general, prognosticate a mid-term increase of the economy indicators. They, in turn, predict a moderate rise of the Bulgarian economic situation. The future values of the factors are interpret and justified and some important implications are drawn in the conclusion of the paper.*

Keywords: *Economy Indicators, Convergence Criteria, Exports & Imports, Harmonized consumer price index, Total business climate indicator, Government balance, Long-term interest rate, ARIMA, NARNN, Forecast .*

INTRODUCTION

The values of the economic indicators are one of the most important barometers for the condition of business, trade and social life in a country. Strategic decisions are taken according them, thus determining the country's economic development. They play a role in attracting new investments and improving the business reputation. What is more, these indicators influence the important national and international political decisions. In particular, to be part of the euro area, Bulgaria must meet formal requirements, which are measured by the degree of convergence of the Bulgarian economy to the ones of the members of the European Union (Kaneva, A., 2018).

In the present work we have considered and analyzed the most significant indicators, which are part of the nominal and the real convergence (Bloomberg TV Bulgaria, 2018). Undoubtedly the indicators reflect the economic situation, i. e. they follow the ongoing economic processes. The value of an indicator is a snapshot describing the economy from certain point of view in a certain time instance and short before it. On the other hand, based on historical data, forecasts are made and critical decisions are taken, which, on their turn, predetermine the tendencies in the economic life. Therefore, the accurate prediction of the important indicators exposes the future state of the economy, and its quality realization is one of the most fundamental problems from both theoretical and practical point of view.

STUDY AIMS

In the present paper we investigate and analyze the expected future values of the part of the Bulgarian economy's most significant indicators, precisely the levels of the exports and imports in BGN, the harmonized index of consumer prices (HICP, previous month = 100[5,6]), total business climate indicator in Bulgaria (observation of business trends in industry, construction, trade and services), total government surplus / deficit as a percentage of the gross domestic product, and the long-term interest rate for convergence assessment purposes. Forecasts are made for the period up to June 2021.

The total exports include all goods meant to leave the statistical territory of the Republic of Bulgaria for normal export to another country. It also includes all commodities, which are returned to the business partner after processing on the territory of the Republic of Bulgaria, or exported / sent for processing on the terriroty of another country and returned back to the Republic of Bulgaria. The value of the export is the value of the goods at the country border crossing, using their values by FOB[7].

The total imports include all commodities, which enter the statistical territory of the Republic of Bulgaria from other countries and are intended for consumption in the country or processing in the country for export to another country as well as imported goods after being processed outside the country. Subject of import could be physical or nonphysical values as electricity, software, patents and licenses, securities, local and foreign currency, gold and other precious metals, but they do not contribute to the import, according to the national statistics. The import itself helps for specialization of manufacture, but, on the other hand, could hinder the development of the local economy if it is not prepared for exogeneous competition. Ususally the State establishes tighter control over the import than the export via duty and the so-called nontariff means of regulation as licenses, quotas, and tax control over importers.

In trading within EU, the statistical value usually differs from the contracted sum (invoice value) due to the different conditions on delivery, used in the deal. Therefore, the statistical value should be evaluated by means of other variables as delivery details and type of transport. Commercial operators are obliged to declare that value only above the threshold of the statistical value. In deals, contracted below the threshold, the statistical value is calculated on the base of the invoice values, delivery conditions, type of transport and contracting country.

The harmonized index of consumer prices (HICP) is a comparative measure of inflation across the EU member states, covering the end monetary customer expenditures of residential (Bulgarian) households, including the institutional (collective) households and the spenditures of nonresidential (foreign) citizens on the economical territory of the country in compliance with the domestic concept for consumption, and excluding the expenditures of the residential (Bulgarian) households abroad and the expenditures for customer goods intended for business. It is one of the criteria for price level stability and a condition for joining the euro area. It measures the total relative change of prices of the commodities and services.

The total business climate indicator is weighted average of the four business climate indicators – in industry, construction, retail and services, where the latter is included in the total dynamic series from May 2002. It is published on national level for the territory of the Republic of Bulgaria. The business climate indicator in the observed industry branches is geometric average of the rates of the present and expected business situation in the companies. The answers in the questionnaries are presented in three-stage category scales as "raise", "no change", "decline" or "more than enough", "enough", "insufficient". The balance of opinions is calculated as the difference between the relative shares of extreme types of answer. Part of the latter is given in numerical grade, for instance production supply with orders (number of months), capacity load (%) and others.

[5] From 2013 NSI applies the detailed Classification of Individual Consumption by Purpose (COICOP-5).
[6] In compliance with Commission Regulation (EU) № 2015/2010, from the beginning of 2016 the base year for HICP has been changed and all indices are calculated and published at 2015 as a base year. The change of the base year of HICP leads to revision of the inflation rates due to rounding. Because of this fact, the inflation rates, calculated from the time series at base 2005 = 100 could differ from those calculated from the series at base 2015 = 100.
[7] FOB / Free On Board = Franco on Board = Freight on Board (agreed origin port).

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The long-term interest rate for convergence assessment purposes (LTIR) is provided on the base of the yield on the maturity on the secondary market of securities (benchmark) issued by the Ministry of finances (subsector Central Government) and denominated in the national currency. The ISMA formula and the day count convention ACT/365 are used. The EU members are calculating the long-term interest rate for convergence assessment purposes, which is defiend according Article 140 of the Treaty establishing the European Economic Community and Article 4 of the Protocol (№13) on the convergence criteria. The methodology requirements for determination of the long-term interest rate are developed by the European Central Bank (ECB, 2020).

The total government deficit / surplus is the balance position of sector General Government and together with the government debt constitute two of the criteria for membership in the European Economic and Monetary Union (the so-called Maastricht criteria). The deficit / surplus of the sector General Government is measured with the net borrowing (-) or net lending (+) loans. The government debt includes all financial liabilities, taken on the behalf of and at the expense of the State. The consolidated gross debt of the sector General Government is presented in nominal value in total and by category and is due at the end of each year.

The main aim of the present work is to consider the current levels of the most significant economic indicators and to forecast their future values via application of mathematical methods (Hyndman, R., 2013), thus presenting quantitive analysis of the trends and dynamics in the Bulgarian economy. The methodology used is a combination of several methods, in particular empirical analysis and comparative analysis. The analytical approach is applied since it brings higher objectivity to the results.

INTRODUCING THE MODELS

The models used in the following analysis aim to forecast the values of the respective economic indicators for a couple of future moments. The historical data for a certain indicator is viewed as a time series, and the future values are found via application of contemporarty methods from econometrics (Enders, W., 1995; Mills, T., 1990; Tsay, R., 2010) and machine learning (Russel, S., et. al., 2020; Smith, K., et. al., 2000). The more significant advantages of the present approach are as follows. Firstly, the subjective factor is almost completely eliminated (except the choice of models). Furthermore, the interpretation of the economic and political events is only implicitly incorporated in the last values of the time series. The latter, depending on the point of view, could be also considered as a drawback, and attempt would be made to overcome it through interpretation of the results in the discussion afterwards.

ARIMA (AutoRegressive Integrated Moving Average)

The autoregressive, integrated, with moving average or $ARIMA\,(p, d, q)$ models are generalization of the models of auroregressive moving average ($ARMA$), where, based on historical time series data, the future values of the series are forecasted (Box, G., et. al., 1994). The autoregressive element p represents the model dependence on p lagged data moments. The integration moment d represents the number of differences applied in order to transform the data into a stationary series, and the element q shows the number of terms needed to smooth out small fluctuations by means of moving average. Usually the time series analysis is conducted in three steps: identification, evaluation and diagnostics.

$ARIMA$ processes generate nonstationary series, integrated of order d, denoted with $I(d)$. A nonstationary $I(d)$ process is a process that could be transformed into a stationary one via d times of differencing. Such processes are often called difference-stationary or unit root processes. A time series which could be modelled as a stationary $ARMA(p, q)$ process after being differenced d times is denoted with $ARIMA(p, d, q)$. It could be written in the following form:

$$\Delta^d y_t = c + \phi_1 \Delta^d y_{t-1} + \ \dots \ + \phi_p \Delta^d y_{t-p} + \varepsilon_m + \theta_1 \varepsilon_{t-1} + \ \dots \ + \theta_q \varepsilon_{t-q}, \qquad (1)$$

where $\Delta^d y_t$ is the d-th order differenced time series and ε_t is a uncorrelated innovation process with zero mean.

Since the autorgressive element suggests a linear regression model for the lags as predictors, it is important for the time series to be stationary. The most used approach to achieve this is to difference the series. It is the value of d that shows how many times the differences should be performed. Often it is done more than once. Easily seen from (1), p is the number of lags used as predictors, and q is the number of error terms, included in the model.

For analysis purposes, we will apply the following algorithm:

1. If the data variance is increasing with time, a logarithmic substitution is applied.
2. If there is a distinct linear trend, it is eliminated[8]. This does not change substantially the data properties.
3. Until the data is nonstationary, we apply difference between adjancent elements (with lag 1). It could be done 0, 1 or several but not many times.

After each differencing, the stationarity of the data is checked[9]. We use augmented Dickey–Fuller test: ADF (Dickey, D., & Fuller, W., 1979) and Kwiatkowski–Phillips–Schmidt–Shin test: KPSS (Kwiatkowski, D., et. al., 1992). The null hypothesis of the first test is that the data is nonstationary. If the p-value is greater than 0.05, then the null hypothesis is accepted and another differencing is needed. However, the null hypothesis of the second test says the data is stationary and we should work towards accepting it.

4. Then we go to the modelling itself. $ARIMA$ models with $d = \overline{0,2}$ and $p, q = \overline{1,4}$ are calibrated and it is decided which spacification fits best the particular time series based on the information critera of Akaike: AIC (Akaike, H., 1974) and Bayesian: BIC (Schwarz, G., 1978). They describe the calibration *goodness-of-fit* and the simplicity of the model in terms of the number of the calibrated parameters. The values of the information criteria must be as lower as possible.
5. If the data is present on a monthly basis, it it natural to expect certain behavior within a year regardless of the development through years. This phenomenon is called *seasionality* and the model is required to reflect it. To achieve this, we will compare the best $ARIMA$ model with the respective $SARIMA$ model, derived in analogous manner to Step 4.

Remark. The most suitable values of p and q could be visually identified from the graphs of the partial autocorrelation functions (PACF) and correlation functions (ACF), respectively. The visual method is difficult to apply when the calibration process is needed to be automated.

Remark 2. The fact that we calibrate models only with small values of d should not raise concern. If the time series is underdifferenced, this is corrected by increasing the AR parameter (p). If the series is overdifferenced, it is compenstaed by increasing the MA parameter (q). Of course, these adjustments are incorporated in the calibrated values.

As shown, most of the economic indicators are given on a monthly basis. On Step 5 of the algorithm we will use $SARIMA$ models, where we add terms including the SAR parameter P, the SMA parameter Q, the number of seasonal differences D and the degree of seasonal differencing polynomial x (Findley, D., et. al., 1998) to the right hand-side of (1). Of course, due to the number of months in the year, $x = 12$. There exists a rule of thumb that $D \leq 1$ and $d + D \leq 2$. This means that the best $ARIMA$ model would be compared to a $SARIMA$ model with $D = 1$ for the indicators on a monthly basis. The identification of P and Q is done in analogous way to Step 4 of the

[8] There are a couple of approaches to detrend a series, including subtracting the mean value or appropriate filtering. In the paper it is adopted the one which requires subtracting the best (in the sense of least squares) straight line, fitted to the data.

[9] Rigourously speaking, the tests check for unit toot absence. The presence of such a root indicated that the time series is not stationary, but the converse is not true (Palachy, S., 2019).

algorithm, and the examined values are $P, Q = \overline{0,6}$.

The algorithm will be performed over the aforementioned time series.

NARNN (Nonlinear AutoRegressive Neural Network)

The nonlinear autoregressive problems require the forecasting of future values of a particular time series given past values of the same series:

$$y_t = f\left(y_{t-1}, y_{t-2}, \dots, y_{t-fbD}\right). \tag{2}$$

Such an approach is often applied in predicting financial time series, for example. To implement it, dynamic neural networks are used, which are a special case of the artificial neural netwoks. The latter are computational systems inspired by the biological neural network, imitating an animal brain. The artificial neural network consists of artificial neurons, mimicking the neurons in brain. The neuron could receive signals, transform them and transmit them. The signals are real numbers, and the trasformation is a real function that acts on the weighted sum of the input signals. The weights represent the strength of the connections between individual neurons. The latter are grouped into layers, as a neural network is composed by an input layer, a zero, one or more hidden layers, and an output layer. The signal is processed from the input to the output layer (when the network is open-loop), and it is possible for the signal to circuit through the layers several times (when the network is closed-loop).

The calibration of the weights of the connections between the neurons is called training of the neural network. The training is conducted via measuring the differences between the “correct” solutions to the given problem and those (2) obtained at the output of the network, defined as an error. The purpose of the weight adjustment is to minimize the error. In this paper we use a special case of this model, which is called supervised learning.

The standard NAR network is a three-layer neural network, with a sigmoid activation function of the hidden layer neurons and a linear activation function of the output layer neuron.

The usage of the neural networks could be described as follows:

1. The first three steps of the algorithm described above are applied. Another feature of the preprocessing of the input data is that in order for the neural networks predictions to be more efficient, the data is normalized in such a way that the input values lie in the range $[-1,1]$, but this is done automatically by the software.
2. Similar to the previous procedure, different specifications of the neural networks $NARNN(fbD, hLS)$ are calibrated, iterating over the number of the feedback delays (2) $fbD = \overline{2,12}$ and the number of neurons in the hidden layer $hLS = \overline{2, {}^{2}/_{3} * fbD + 1}$ (Stathakis, D., 2009; Kihoro, J., et. al., 2004). At this stage, an open-loop network is used. Block division of the time series into training, test and validation subsets is applied. The Levenberg – Marquardt algorithm is used for training, and the mean square error is used as a performance criterion. Each specification is trained 5 times and the average performance is taken into consideration. Finally, the configuration with the lowest average performance indicator is selected.
3. The network with the best performance is closed, i. e. transformed into a closed-loop network. It is trained 20 times and each time a forecast is made. The average of all forecasts is considered as the final forecast.

Two efficiency increasing techniques are implemented in the latter algorithm, in particular to prevent the neural network from overtraining. Firstly, it is examined those combinations of parameters which might lead to the best results, while each network configuration is trained several times, respectively with different random initial weights. This allows us to study the performance of a particular network in more depth, without being misled by any accidental good result. Secondly, the best configuration is converted into a closed-loop network, which is again trained a couple of times. We have already guaranteed the efficiency of the network, and now the different instances "vote" for the predicted values and their "votes" are being averaged to obtain the final forecast. It is possible to weigh the network forecasts proportionally to their performance indicators, but this does not lead to a significant change in the results, as all representatives are instantiated from the best configuration.

Next, the application of the two algorithms on each economic indicator data follows.

Exports – FOB (total, to EU and third countries)

The data is presented on a monthly basis, from January 2009 to June 2020, which equates to 138 values. Our goal is to predict the behavior of the indicator for the next 12 months.

First we apply logarithmic substitution, then we eliminate the linear trend. The ADF test "votes" for data stationarity, but the KPSS test does not yet confirm this. We difference the series once and only after it, the data could be interpreted as stationary. The specification $ARIMA$ (3,0,4) is the most appropriate model, as it has the lowest values of the information criteria.

Because the data is given on a monthly basis, we also check the potential $SARIMA(3,0,2) \times (P, 1, Q)_{12}$ models. Since $D = 1$, the difference with the 12^{th} lag is included in the model. The values of the information criteria of the $SARIMA(3,0,4) \times (5,1,4)_{12}$ model are lower than values of the previous one, so we accept it for a forecast analysis.

The $NARNN$ (11,5) model is with lowest indicator of performance. The forecast of the models could be viewed in Figure 1. It shows a steady rise in the level of exports, and the steepness is similar to the slope of the trend. Of course, the different initialization of neural network weights result in similar but not precisely the same outcomes. This suggests that the forecast of neural networks (red in the graph) shows the direction and pattern of development, but not the precise values to be achieved by the respective indicator.

Imports – CIF (total, to EU and third countries)

The data is similar to that for exports – on a monthly basis, from January 2009 to June 2020. Again, we have to utilize the first three points of the algorithm, i. e. to apply logarithmic substitution, to detrend the data and to difference it once.

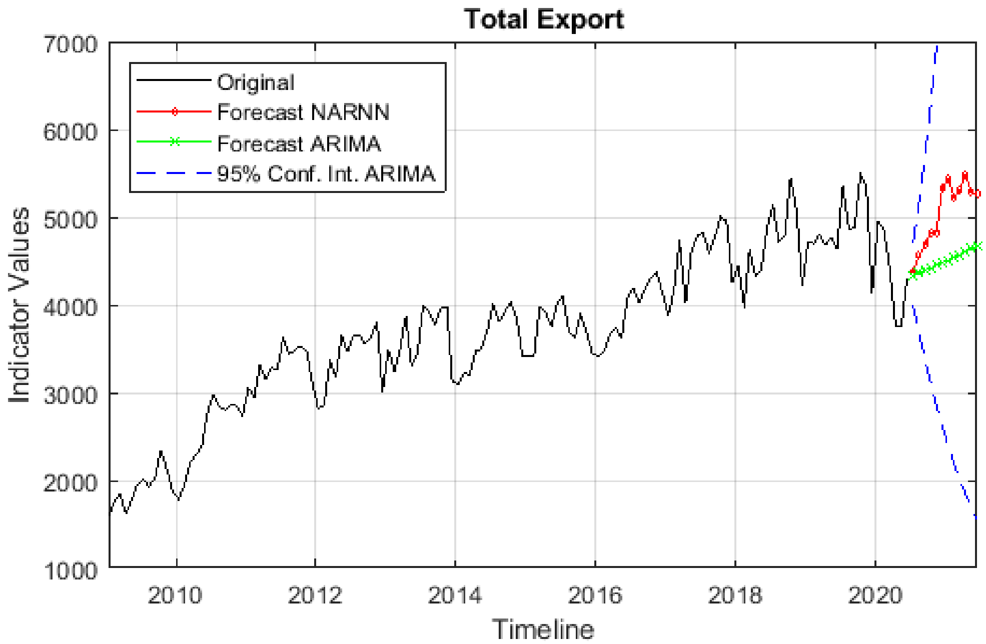

Figure 1. Total exports - FOB.

The $ARIMA(2,0,4)$ model is the most suitable calibration of the nonseasonal specifications. From the seasonal ones it turns out to be $SARIMA(2,0,4) \times (7,1,2)_{12}$ and as expected, the values of its information criteria are lower than those of the nonseasonal counterpart. $NARNN$ (12,8)

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model is the most appropriate model for prediction. The forecast is presented on Figure 2, which is similar to that of total exports. A distinct increase in the level of imports is expected. It is noteworthy that in nominal terms imports are higher than exports.

Harmonized index of consumer prices

HICP data is again available on a monthly basis, from January 2014 to August 2020. This equates to 80 values. Due to the negative values, the time series obviously could not be logarithmized. Although both tests allow working with the original data, we eliminate the trend thus obtaining better results. On the other hand, we do not difference the series unnecessarily.

$ARIMA(3,0,3)$ is obtained for the best specification from the nonseasonal models, and from the seasonal analogues – $SARIMA(3,0,3) \times (4,1,1)_{12}$. Again, the values of the information criteria for the seasonal model are lower. However, it should be noted that although the AIC and BIC are negative for the $SARIMA$ model, they are much higher than the ones of the previous economic indicators. This is due to the smaller amount of information, i. e. the shorter time series.

The model $NARNN(9,6)$ has the best performance indicator. The forecasted data might be observed in Figure 3. HICP values are expected to maintain their development tendency and to slightly increase compared to their level from August 2020. Despite the small width of the confidence interval, strongly oscillating values around the mean should not be surprising. As we will comment later, the fluctuations are determined by the cycles of imposing and loosening the anti-epidemic measures, which directly affect consumption and production.

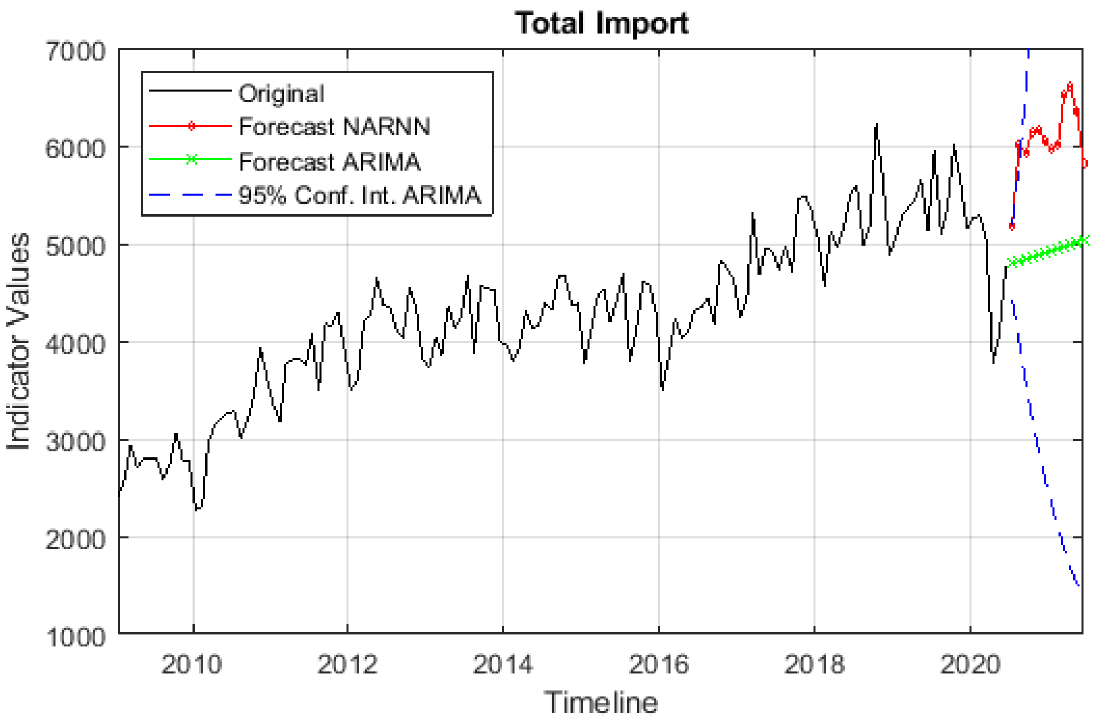

Figure 2. Total imports - CIF.

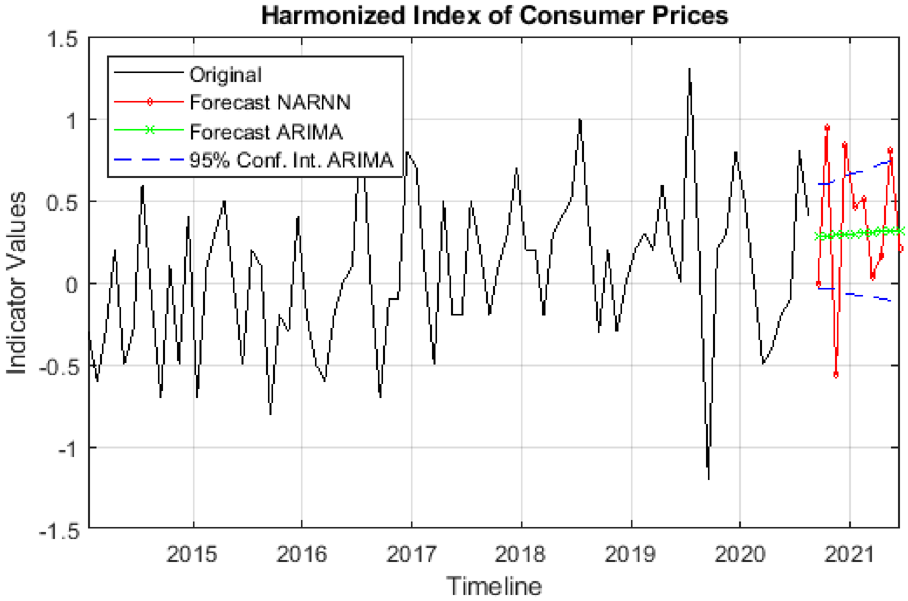

Figure 3. Harmonized index of consumer prices.

Total business climate indicator

The values of the total business climate indicator are presented on a monthly basis, from January 1997 to September 2020 – 285 values. Here again the time series could not be logarithmized. According to both tests, the data in its original form is not stationary. Detrending also does not station the data according to the KPSS test, while the differencing is sufficient for the series to be considered as stationary.

$ARIMA(3,0,3)$ is the most appropriate calibration from the nonseasonal models, and from the seasonal analogues $- SARIMA(3,0,3) \times (6,1,5)_{12}$. The $NARNN$ (9,4) specification is the best from the neural network models. It should be noted that the values of the performance indicator are slightly higher, which might mean a small uncertainty in the forecast.

It could be examined on Figure 4. The average forecast of the neural networks does not show determination in any direction. On the other hand, the forecast of the $ARIMA$ models confirms the other, which suggests the preservation and a very slight increase of the total business climate indicator compared to the level of September 2020.

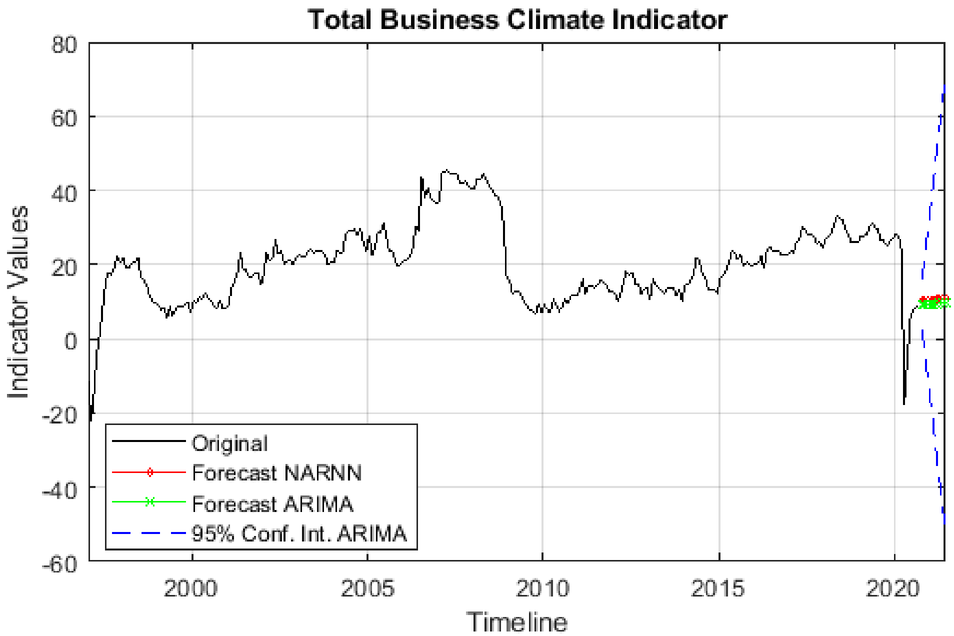

Figure 4. Total business climate indicator.

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Total government deficit or surplus as a percentage of the gross domestic product

The data of the total government deficit or surplus is given on an annual basis. In Eurostat[10] could be found information from 2008 to 2019. This means working with 12 values, which assumes an unreliable analysis. Therefore, we will manually calculate the indicator for previous periods. From Infostat[11,12], we extract data for the government deficit or surplus as net borrowing (-) or net lending loans (+) by subsectors of General Government. Then we download the data for the gross domestic product – production approach, and divide elementwisely the first indicator to the second one (both are given in millions of BGN). We now have data from 1997, which results in 23 observations.

Due to the annual base, it does not make sense to expect seasonality in the series. What is more, it could not be logarithmized. We eliminate the linear trend. According to the KPSS test, the data in this form is not stationary. After a single differencing, both tests confirm the stationarity of the data.

Calibration of the models leads to the specification $ARIMA(1,0,1)$. The values of the information criteria are small, but they are still positive, which could be interpreted as a not so good fit of the model. This could be observed by the large width of the confidence interval, and it is due to the small number of elements in the series.

The model $NARNN(12,6)$ proves to be the most appropriate. Here, again, the value of the performance indicator is relatively higher than those accountered in the evaluation of the other economic indicators, which again implies that the analysis should be accepted with some reservations. The forecast could be observed on Figure 5.

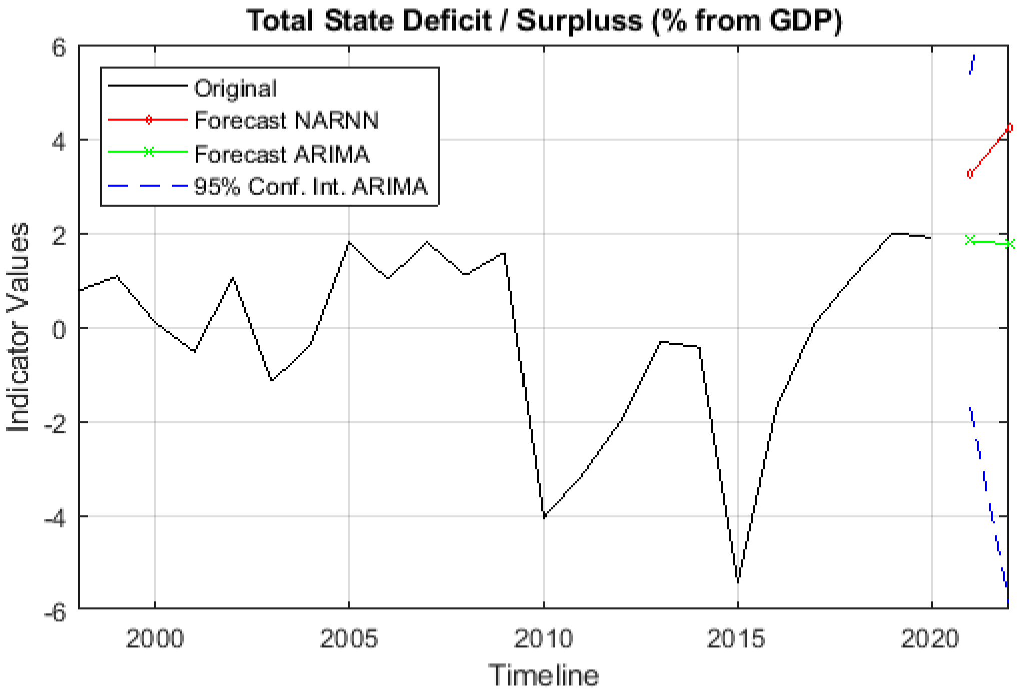

Figure 5. Total governmnet deficit or surplus as a percentage of the GDP.

Doubts about the results might also arise from the fact that in this case the forecasts do not match. Moreover, this is the only indicator on an annual basis, and since the last value is from last year, the data do not contain information for the economic consequences of the epidemic and the political decisions related to it.

[10] https://ec.europa.eu/eurostat/tgm/refreshTableAction.do?tab=table&plugin=1&pcode=teina200&language=en
[11] https://infostat.nsi.bg/infostat/pages/reports/query.jsf?x_2=699
[12] https://infostat.nsi.bg/infostat/pages/reports/query.jsf?x_2=1169

On the other hand, when calibrating $ARIMA$ models over data since 2008, the prediction of the best $ARIMA(6, 2, 3)$ specification (see Figure 6) completely coincides with the one of the neural networks.

The results, as it will be discussed later, could be interpreted as follows. In an economic situation similar to last year's, e. g. if there is no epidemic or it does not significantly affect the economy, we could expect a steady increase in the government surplus as a percentage of GDP. As this is not the case, the forecast for a moderate reduction in the surplus is more plausible.

Long-term interest rate for convergence assessment purposes

Interest rates are given on a monthly basis, from January 2003 to August 2020 – 212 observations. Interestingly, both tests require logarithmic change, linear detrending and differencing to confirm the absence of unit roots. Also, the volume of the data suggests a reliable predictive analysis.

$ARIMA(4,0,4)$ turns out to be the best specification. From the seasonal models the algorithm outputs $SARIMA(4,0,4) \times (10,1,5)_{12}$. The neural network calibration suggests $NARNN(4, 3)$ as the most appropriate.

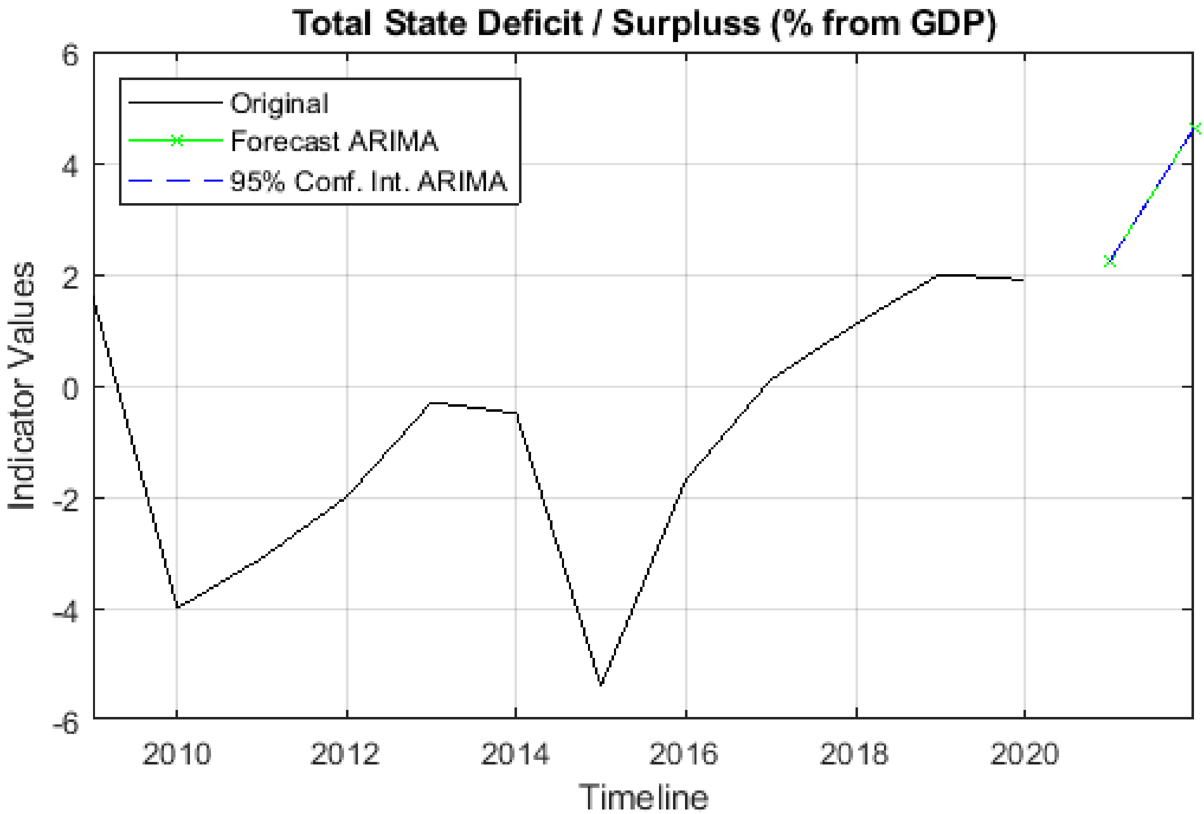

Figure 6. Total government deficit or surplus as a percentage of the GDP (with scarce data).

The forecast is presented in Figure 7, and the conclusions are that we could expect a retention and a slight decrease in the long-term interest rate compared to the level of August 2020. Due to the logarithmization of the series, the prediction of negative values is out of the scope of the models, but it is clear that a decrease in the percentage level is most likely to happen.

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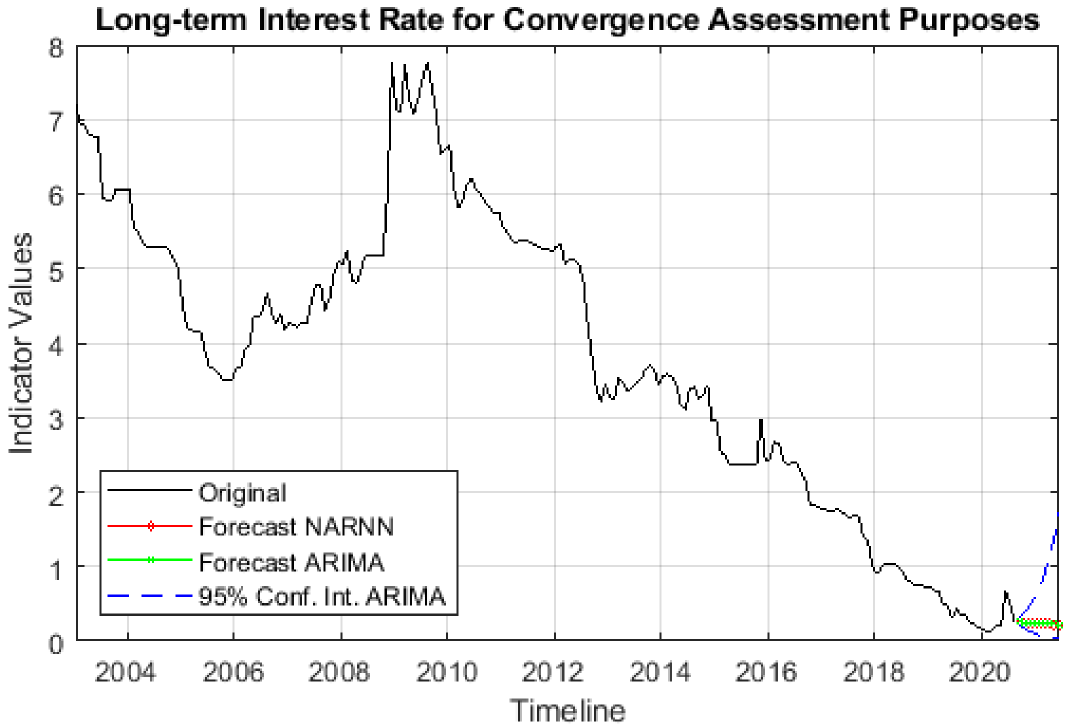

Figure 7. Long-term interest rate for convergence assessment purposes.

INTERPRETATION OF RESULTS

The forecast of the future values of the studied parameters is valid for similar to the current economic and market conditions. The presented models are efficient in steady economic conditions, and in this sense it is worth noting that even in a change of economic and market system, preceded and followed by high and unstable market volatility, after normalization of the situation or after a sufficient duration of the chaotic market situation, the necessary data could be gathered in order to apply the above models efficiently.

Figure 1 presents the forecast estimates of the total exports of the Republic of Bulgaria to the EU and third countries. The forecast of the model shows a steady increase in the level of exports, as the slope is identical to that of the trend. Although the values of the information criteria and the performance indicator are very low, the large width of the confidence interval is impressive, where in the forecasts of the future values the upper limit is above the maximum historical value of exports and the lower limit is close to the minimum historical value of exports. Taking into account the estimated forecast and the accompanying confidence interval, it could be concluded that under stable economical and political conditions, Bulgaria's exports are expected to continue their trend of positive development and to increase their level. However, there is a high risk for the sustainability of this trend. To put it in other words, the expected positive trend could easily be significantly influenced by changes in the current economic (especially market) and political conditions, both negatively and positively, depending on the management decisions made.

A similar interpretation of the results of exports could be made for the total imports (to EU and third countries) of the Republic of Bulgaria. Figure 2 presents the predicted values of the total imports of the Republic of Bulgaria, which is partially a function of exports. The forecast is similar to that of total exports. So far, imports have been higher than exports. In this sense, also taking into account the large width of the confidence interval, the following statement could be made: the expected trend of imports is positive, partly due to the fact that imports are partially a function of exports. Moreover, it is forecasted that imports might grow slightly faster than exports, and the superiority of imports would be maintained for the projected time interval. Here again the presence of high risks to the sustainability of this trend gives a rise to doubts that it might not be stable, but fluctuate around the mean.

Figure 3 presents forecast estimates of the harmonized index of consumer prices for the Republic of Bulgaria, which is a comparative measure of inflation. In the coming months, prices of goods and services are expected to rise, considering the consumption of all households, including institutional (collective) and foreign households in the country. It is noteworthy that the distance between the borders of the confidence interval is not too large, despite the high volatility, from which the following conclusion could be drawn: increases and decreases in HICP values could be observed, but nevertheless the long-term trend indicates an increase in the value of the inflation. As already mentioned, the individual fluctuations are directly dependent on the introduced anti-epidemic measures, on their intensity, duration and impact on the economy.

Figure 4 presents the forecasts of the future values of the total business climate indicator. It should be noted that it is a weighted average of the four branch indicators of the business climate – in industry, construction, retail and services sector, and any change in the economic and political conditions would affect both exports and imports thus the total business climate indicator. The forecast predicts a very slight increase of the total business climate indicator compared to the level of September 2020. In this case, there also could be observed a wide confidence interval, probably due to the increase in the volatility of the indicator in recent months. On the other hand, the “linear” prediction of neural networks is a signal that there might be a “disagreement” between the different networks’ opinions on the amplitude of the changes. Accordingly, there is a risk of a abrupt change or jump in the value of the indicator, which could be both up and down. It could be stated that such a change would be strongly proportional to changes in exports and imports.

The forecast for the future values of the government surplus or deficit as a percentage of GDP is depicted on Figures 5 and 6. The first thing that makes an impression is that the two forecasts diverge in the direction of development of the indicator. On other hand, as the indicator is on an annual basis, the events and their manifestations from the last year are not incorporated in the data. We could conclude that if economic life lacks the effects of the crisis caused by the epidemic and the measures to restrain it, we could expect a steady increase of the budget surplus. Such a strong increase in the surplus is not a positive signal, as it speaks of incompetent planning of government revenues and expenditures. However, this scenario is far from the real situation. Measures such as financial aid and benefits have been taken to address the economic consequences, increasing total government spending. In this case, the reasonable forecast is to expect a slight reduction in the budget surplus.

The forecast of the long-term interest rate trend for convergence assessment purposes is presented in Figure 7. A preservation and a slight reduction of the long-term interest rate could be expected compared to the level of August 2020. As we mentioned, although negative LTIR values could not be predicted, they could be observed (Nonchev, I., 2019). Here, again, there might not be a complete “consensus” among the neural networks on the dynamics of the development of the time series, but the forecasts confirm the long-term reduction of the interest rate.

As a summary of the exposed forecasts, it could be argued that in stable economic and political circumstances in the near future the Republic of Bulgaria expects favorable economic development, leading to an improvement of the key economic indicators. Attention must be paid to the susceptibility of these indicators to political and market shocks, which might be a subject of more in-depth further study. A better assessment could be obtained with an individual detailed risk analysis for each economic indicator, which is subject of future research.

Given the current situation in the country, Europe and the world, we should expect cyclicity in the performance of the indicators, caused by the periods of tightening and loosening the measures preventing the spread of the epidemic. The information about these measures, taken in the first half of this year, is implicitly incorporated in the latest values of the indicators on a monthly basis. An example of such a phenomenon could be observed in the neural networks forecast of HICP, although it is not reasonable to rely on the precise trajectory.

When the measures are relaxed in the main commercial partners from Europe, USA, Russia, China and other large countries, this could have a favorable effect on trade, respectively on exports,

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imports, etc. The indicators are interrelated, for example, the imports are also influenced by domestic consumption, respectively by the situation in the country. Conversely, demand decreases as measures are tightened, and this has a negative effect on the indicators. Of course, the measures could not be constantly relaxed or cancelled, as this would cause a breakdown in the healthcare system. Political decisions are constantly being taken on whether to tighten or loosen measures, including whether to impose throughout quarantine in different parts of the country, depending on the spread of the epidemic.

If these solutions prove to be prompt and appropriate, it is reasonable to expect an improvement in the economic environment and a corresponding increase in the economic indicators considered, despite the time of global economic stagnation caused by various factors.

CONCLUSION

In the present study an algorithm for automated evaluation and prediction of the most significant indicators of the Bulgarian economy is proposed. Forecasts of the values of total exports and imports, the harmonized index of consumer prices, the total business climate indicator, the total government deficit or surplus as a percentage of the gross domestic product and the long-term interest rate for convergence assessment purposes are presented, and estimates for the future values are made up to June 2021.

The general conclusions are that if the economic conjuncture stays relatively unchanged, we could expect a favorable development of the market environment, which has a positive impact on the economical indicators. Of course, there is a considerable risk for the stability of the trend, which could be easily disrupted depending on the spread of the epidemic and subsequent «non-pharmaceutical» interventions in the economical life of the country and its commercial partners.

In conclusion, we would outline the ways in which the present study could be continued. On the one hand, as mentioned earlier, the risk associated with each economic indicator could be examined. It is worth paying attention also to the long short-term memory (LSTM) artificial recurrent neural networks, which are especially well suited to make predictions based on time series data. Moreover, approaches that predict the future values of an indicator based on its historical values and on other indicators could be applied in forecasting, solving the so-called problems with external (exogenous) input. Such models are $(S)ARIMAX$ and $NARXNN$, respectively. There is a great potential in such a problem, because, as we have already noted, the values of the indicators are to a certain extent dependent on each other due to the fact that they reflect different characteristics of the same system.

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REFERENCES

Akaike, H. (1974). *A New Look at the Statistical Model Identification.* IEEE Transactions on Automatic Control, 19(6), 716-723.

Bloomberg TV Bulgaria. (2018). *Real convergence – the fictional criterion for joining the euro area.* URL: https://www.bloombergtv.bg/a/4-analizi/23794-realna-konvergentsiya-izmisleniyat-kriteriy-za-vlizane-v-evrozonata (Accessed on 15.10.2020) (***Оригинално заглавие:*** *Реална конвергенция – измисленият критерий за влизане в еврозоната.*)

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (1994). *Time Series Analysis: Forecasting and Control.* 3rd ed. Englewood Cliffs, NJ: Prentice Hall.

Dickey, D. A., & Fuller, W. A. (1979). *Distribution of the Estimators for Autoregressive Time Series with a Unit Root.* Journal of the American Statistical Association, 74(366), 427-431.

Enders, W. (1995). *Applied Econometric Time Series.* Hoboken, NJ: John Wiley & Sons, Inc.

European Central Bank. (2020). *Convergence criteria.* URL: https://www.ecb.europa.eu/ecb/orga/escb/html/convergence-criteria.en.html (Accessed on 15.10. 2020) (***Оригинално заглавие:*** *Критерии за конвергенция.*)

Findley, D. F., Monsell, B. C., Bell, W. R., Otto, M. C., & Chen, B.-C. (1998). *New capabilities and methods of the X-12-ARIMA seasonal-adjustment program.* Journal of Business & Economic Statistics, 16(2), 127–152.

Hyndman, R. J., & Athanasopoulos, G. (2013). *Forecasting: Principles and Practice.* OTexts.

Kaneva, A. (2018). *Estimate of the convergence degree of the Bulgarian economy with the European union member countries in the period 2004-2016.* Economic and social alternatives, 1, 69-89. (***Оригинално заглавие:*** *Кънева, А., 2018. Оценка на степента на конвергенция на българската икономика с икономиките на страните – членки на Европейския съюз, през периода 2004-2016 г. Икономически и социални алтернативи, 1, 69-89.*)

Kihoro, J. M., Otieno, R. O., & Wafula, C. (2004). *Seasonal time forecasting: A comparative study of ARIMA and ANN models.* African Journal of Science and Technology, Science and Engineering Series, 5(2), 41-49.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P, & Shin, Y. (1992). *Testing the null hypothesis of stationarity against the alternative of a unit root.* Journal of Econometrics, 54, 159-178.

Mills, T. C. (1990). *Time Series Techniques for Economists.* Cambridge University Press.

Nonchev, I. (2019). *Whether the credit interest rates would decrease when we join the euro area?* Profit.bg. (***Оригинално заглавие:*** *Нончев, И., 2019. Ще паднат ли лихвите по кредитите, когато влезем в еврозоната?*)

Palachy, S. (2019). *Stationarity in time series analysis.* towardsdatascience.com.

Russel, S., & Norvig, P. (2020). *Artificial Intelligence: A Modern Approach.* 4th edition, New Jersey: Pearson Education, Inc.

Schwarz, G. (1978). *Estimating the Dimension of a Model.* The Annals of Statistics, 6(2), 461-464.

Smith, K. A., & Gupta, J. N. D. (2000). *Neural networks in business: techniques and applications for the operations researcher.* Computers & Operations Research, 27, 1023-1044.

Stathakis, D. (2009). *How many hidden layers and nodes?* International Journal of Remote Sensing, 30(8), 2133-2147.

Tsay, R. (2010). *Analysis of Financial Time Series.* Third Edition, New Jersey, John Wiley & Sons, Inc.

