Using Artificial Neural Networks To Forecast Gdp For Turkey

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Abstract

Artificial Neural Networks (ANN) is a system resembling biological neural systems and uses working principles of human brain as a base. ANN can be applied in various fields for the purposes of forecasting, classification, optimization, data binding and so on. ANN has been frequently used in financial applications in recent years. In this study, ANN is used in forecasting Gross Domestic Product of Turkey. Gross Domestic Product (GDP) refers to the market value of all final goods and services produced within a country in a given period. GDP can be thought as the size of an economy and it is the foremost important measure of macroeconomic performance of a country, a country's health and standard of living. Therefore, expectations about future GDP can be the primary determinant of investments, employment, wages, profits and even stock market activities. With respect to its economic

significance mentioned above, the purpose of this study is to forecast Gross Domestic Product (GDP) for Turkey and to test the ability of ANN Method in forecasting GDP.

Keywords: Importance of Gross Domestic Product, Forecasting, Artificial Neural Networks.

1. INTRODUCTION

Gross Domestic Product (GDP) is the total market value of all the final goods and services produced within a country's boarders in a given year. This production is generated by both citizens of the country and foreigners living in its borders. GDP is one of the most important indicators of an economic growth, health and welfare. Therefore, it tells us a lot about the real economic activity.

Calculation of GDP can be basically done in one of two ways: either by adding up what everyone earned (income approach), or by adding up what everyone spent (expenditure method) in a year. Logically, both measures should arrive at roughly the same total (www.investopedia.com). In Turkey, GDP is measured quarterly by TUİK. To compute economic growth, each quarter is compared to the previous one.

Considering its large impact on almost everybody in an economy, forecasting GDP has a great importance both theoretically and practically. First of all, GDP represents economic production and growth. So it gives a signal about the future employment and wages. GDP also determines stock market return rates. If GDP growth rate is positive, then investors may expect to gain revenue (www.investopedia.com).By using GDP reports, it can be seen which sectors of the economy are growing and which ones are declining. This would help investors to determine whether they should invest in or which sectors they should invest in (http://useconomy.about.com/od/grossdomesticproduct/p/GDP.htm).

The GDP statistics can help the economists a lot in solving the problems of inflation in the country. The national income figures throw light as to how much general price level has increased or decreased, how much of their income people spend on consumption goods and how much they save? Government can devise measures of controlling inflation or deflation on the basis of these figures of consumption, saving and investment in the country (http://www.economicsconcepts.com/gdp_as_a_measure_of_welfare.htm).

In the existing literature, forecasting GDP is widely studied with different methods. In this paper, we wish to determine whether the forecasting performance of this variable can be improved using neural network models. In this context, the purpose of this study is to forecast GDP of Turkey using Artificial Neural Networks (ANN) Method. The rest of this paper is organized as follows: Section 2 reviews some of the literature on GDP forecasts. Section 3 describes the methodology, while Section 4 presents the results. Finally, section 5 concludes the paper.

2. Literature review

Tkacz and Hu (1999) have determined whether more accurate indicator models of output growth, based on monetary and financial variables, can be developed using neural networks. The authors have used ANN model to forecast GDP growth for Canada. The main findings of this study are that, at the 1-quarter forecasting horizon, neural networks yield no significant forecast improvements. At the 4-quarter horizon, however, the improved forecast accuracy is statistically significant. The root mean squared forecast errors of the best neural network models are about 15 to 19 per cent lower than their linear model counterparts.

Marcellino (2007) has evaluated whether complicated time series models can outperform standard linear models for forecasting GDP growth and inflation for the United States. In the study, it is considered as a large variety of models and evaluation criteria, using a bootstrap algorithm to evaluate the statistical significance of the results. The main conclusion is that in general linear time series, models can be hardly beaten if they are carefully specified.

Schumacher and Breitung (2008) have employed factor models to forecast German GDP using mixed-frequency real-time data, where the time series are subject to different statistical publication lags. In the empirical application, the authors have used a novel real-time dataset for the German economy. Employing a recursive forecast experiment, they have evaluated the forecast accuracy of the factor model with respect to German GDP.

Guegan and Rakotomarolahy (2010) have conducted an empirical forecast accuracy comparison of the non-parametric method, known as multivariate Nearest Neighbor method, with parametric VAR modeling on the euro area of GDP. By using both methods for now casting and forecasting the GDP, through the estimation of economic indicators plugged in the bridge equations, the authors have got more accurate forecasts when using nearest neighbor method. It is also proven the asymptotic normality of the multivariate k-nearest neighbor regression estimator for dependent time series, providing confidence intervals for point forecast in time series.

Mirbagheri (2010) has investigated the supply side economic growth of Iran by estimating GDP growth. In this study, the predictive results of Fuzzy-logic and Neural-Fuzzy methods are also compared. According to the findings of the study, forecasting by the Neural-Fuzzy method is recommended.

Ge and Cui (2011) have used process neural network (PNN) into the GDP forecast and established the forecast model based on PNN by choosing the main factors influencing GDP and using the dual extraction capacity on time and space cumulative effect of PNN. By means of comparing and analyzing with traditional neural network forecast model, the result shows that GDP forecast model which bases on PNN has a better performance.

Liliana and Napitupulu (2010) have also used ANN method in forecasting GDP. In this study, authors have forecasted GDP for Indonesia and they put forward many advantages and disadvantages of the method. According to the results, the authors have concluded that the ANN model has better ability in forecasting the macroeconomic indicators.

3. Methodology

Artificial neural networks (ANN) may be identified as computing technologies containing performances and general features of biological neural networks (Deng v.d., 2008:1118). ANN, developed by imitating the human brain's operating mechanism with the aim of realizing the basic operations performed by the brain, is a logical computer programming technique. In a computer media, an algorithm, which attempts to operate as the brain does, makes a decision, makes a conclusion, arrives at a conclusion on the basis of the existing data when data are missing, accepts new data input constantly, learns and remembers, is called as "Artificial Neural Networks".(Kaltakçı, 1997:411-420)

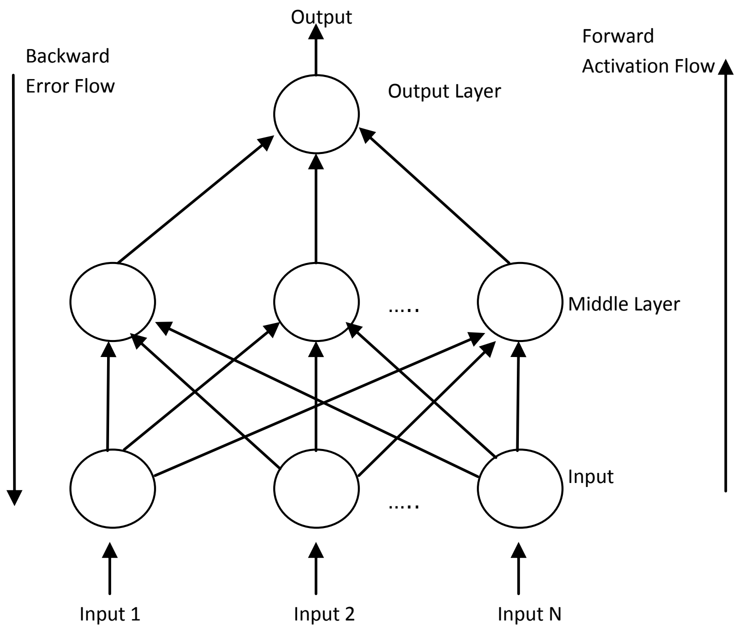
Artificial neural networks consist of many simple processing elements called as nodes or nerves. Each nerve is attached to the other nerves with weights. These weights indicate the information used by the network to solve a problem. Nerves are located in each layer and these layers are interconnected to the other nerves in adjacent layers. A weight gives the mathematical value of the relative power of information's connections that have been transferred from one layer to another. Addition function calculates the sum of all the weighted inputs of a nerve. Activation function is used for the conversion of output in an acceptable range. (usually 0-1 range). Input layer is identified with the independent variables while output layer is identified with the dependent variables (Deng v.d., 2008:1118).

Networks having one layer are called single-layered neural networks while networks having more than one layer are called multilayered neural networks. In a multilayered neural network, number of neurons in each layer may vary (Hines, 1997; 206). While a single-layered network consists of an input and output layer, a multilayered network may consist one or more middle (hidden) layers. As the number of middle layers increases, the ability of artificial neural network to get statistics from input data also increases (Nygren, 2004).

If an artificial neural network is required to solve a nonlinear problem, a more sophisticated type of network is needed for these types of problems. Multilayered sensors (MLS) are network architectures developed for this purpose. This network has a forward network architecture and a supervised learning method is used (Deng, 2008:1118). MLS consists of an input layer, one or more middle layers and an output layers. Each layer has one or more processing elements. All processing elements in a layer is interconnected to all processing elements in a top layer. The flow of information is forwards and there is no feedback. Therefore, these types of networks are called as feed-forward neural network model. There is no information processing in input layer. The number of processing elements in input and output layers is totally dependent on the practiced problem. The number of middle layers and the number of processing elements in middle layers are found by trial and error method (Lippmann, 1987; 24-25).

Each produced output in these types of networks is compared with the target output in each learning iteration and errors are calculated. By propogating backwards in neural network, this error is used to correct the weights. This process goes ahead so long as the mean squared error between target output and output produced by network is minimized (Deng, 2008:1118). For this reason, this type of network is also called as error propogation model or backpropogation network model (Öztemel, 2003:76). These types of networks are illustrated (exemplified) in Figure 1).

Figure 1: A Multilayered Network Model



Kaynak: (Hamid ve Iqbal, 2004:1118)

4. Forecasting Gross Domestic Product with ANN

In this study, by the method of artificial neural networks, the gross domestic product has been estimated on the basis of the calculated data by the method of three-monthly expenditures for the years of 1998-2010. Data have been drawn from the website of Turkish Statistical Institute. In the study, 52 pieces of data have been used for each variable covering the three-monthly periods of 13 years. 20% of the data consists of tests and 80% of it consists of trainings which thus randomly creates 4 different groups.

Gross domestic product consists of a composite of macroeconomic variables such as resident household consumption, government final consumption expenditure, gross fixed capital formation, stock exchanges, export and import of goods and services. Gross domestic product is considered to be dependent variable while household consumption, government final consumption expenditure, gross fixed capital formation, stock exchanges and export and import of goods and services and time are considered to be independent variable. Together with their symbols, the dependent and independent variables used in the study are shown below.

Gross National Product: GDP

Time: T

Resident Household Consumption: RHC

Government final consumption expenditure: GFCE

Gross fixed capital formation: GFCF

Stock Exchanges: SE

Goods and Services Expenditures: GSE

Import of Goods and Services: IGS

In the study, as the values of independents are unknown during the desired terms accept the time variable, GDP ,which is a dependent variable, has been predicted after each independent variable has been estimated separately depending on the time. Namely, each independent variable has been considered as dependent variable and they have been predicted depending on the time variable. Different neuron numbers and hidden layer numbers have been tested to find the most appropriate network which will be used in the prediction of all variables. The estimated performance metrics have been evaluated in determining the most appropriate network. The network structure, of which forecasting measurements are the smallest, is identified as the most suitable one. The most appropriate network structures used to predict the all variables are illustrated in Table 2. Yet, as the stock exchanges, taken as independent variable, have so many sharp rises and falls, each quarter is estimated and combined within itself. The estimation performance metrics; MSE (Mean Square Error), RMSE (Root mean square) and MAPE (Mean absolute percentage error), which are commonly used in the literature, are shown in Formula 1,2 and 3 (Zhang ve Hu, 1998:500, Cho, 2003:328, De Lurgio, 1998:53).

$$RMSE = \sqrt{\frac{\sum (y_t - \hat{y}_t)^2}{T}} \qquad (1)$$

$$MAPE = \frac{1}{T} \sum \left| \frac{y_t - \hat{y}_t}{y_t} \right| \times 100 \qquad (2)$$

$$MSE = \frac{\sum \left(y_t - \hat{y}_t \right)^2}{T} \qquad (3)$$

Here;

y_t = The actual observation values,

$\hat{y}_t$ = Estimated values,

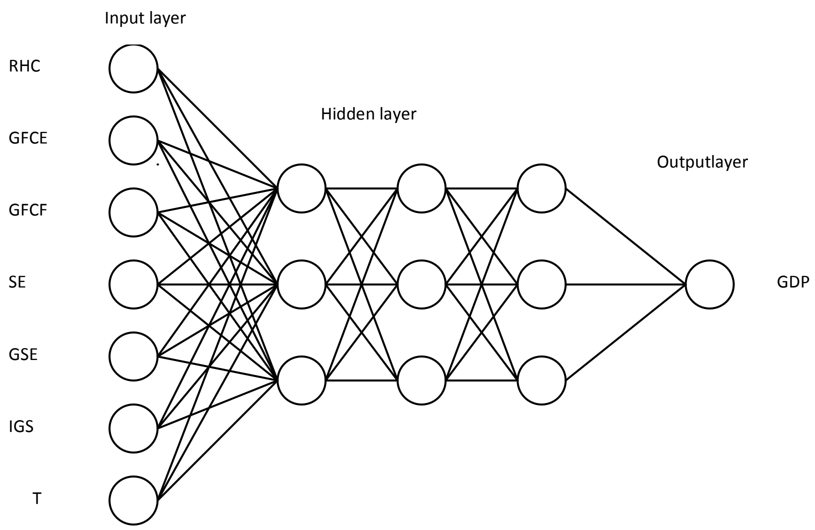
T = Estimated numb

Table1: The network structures used for estimation of variables

<table>
<tr><th colspan="2">Independent variables</th><th>Number of neurons in the input layer</th><th colspan="2">The number of intermidiate layer neurons</th><th>Number of neurons in the output layer</th><th>R^2</th><th>MAPE</th><th>μ (The number of iteration)</th></tr>
<tr><td colspan="2">RHC</td><td>1</td><td colspan="2">3</td><td>1</td><td>0,97</td><td>3,73</td><td>3</td></tr>
<tr><td colspan="2">GFCE</td><td>1</td><td colspan="2">4</td><td>1</td><td>0,96</td><td>3,94</td><td>5</td></tr>
<tr><td colspan="2">GFCF</td><td>1</td><td colspan="2">3</td><td>1</td><td>0,81</td><td>9,32</td><td>10</td></tr>
<tr><td rowspan="4">SE</td><td>SE1</td><td>1</td><td>2</td><td>3</td><td>1</td><td>0,83</td><td>70,5</td><td>20</td></tr>
<tr><td>SE2</td><td>1</td><td colspan="2">3</td><td>1</td><td>0,86</td><td>88,6</td><td>20</td></tr>
<tr><td>SE3</td><td>1</td><td colspan="2">5</td><td>1</td><td>0,78</td><td>6,6</td><td>15</td></tr>
<tr><td>SE4</td><td>1</td><td>2</td><td>3</td><td>1</td><td>0,97</td><td>19,5</td><td>20</td></tr>
<tr><td colspan="2">GSE</td><td>1</td><td colspan="2">2</td><td>1</td><td>0,94</td><td>5,20</td><td>15</td></tr>
<tr><td colspan="2">IGS</td><td>1</td><td colspan="2">3</td><td>1</td><td>0,95</td><td>6,6</td><td>12</td></tr>
<tr><td colspan="2">GDP</td><td>7</td><td colspan="2">3</td><td>1</td><td>0,99</td><td>2,77</td><td>2</td></tr>
</table>

Estimation performance metrics of Gross domestic product (GDP) are obtained as MSE=0,000042, RMSE=0,006451 ve MAPE=2,775746%. On the basis of these measurements, Witt and Witt (2000) classified the estimation models and called those whose MAPE values are under 10% as the models having " high accuracy" and those whose values are between 10% nd 20% as the "correct predictions". Similarly, Lewis classified the models and called those hose MAPE values are less than 10% as "very good", those between 10% and 20% as "good", those between 20% and 50% as "acceptable" and those under 50% as "false and erroneous" (Aktaran, Çuhadar ve Kayacan, 2005:6).

Figure2: The optimum network structure to estimate the GDP



In this study, Matlab 7.9 computer package program has been used. For training function 'trainlm' , for learning function 'learngdm', for performance function 'MSE' and for the transfer function 'tansig' have been selected. In the study, predicted and actual values have been given in Table 2.

Table 2: Actual and Estimated Values of GDP

	Actual(1.000TL)	**Estimated (1.000TL)**
2011 GDP	**85.139.293**	**109.708.230**
2011-Q1	26.205.423	26.070.548
2011-Q2	27.904.922	27.911.332
2011-Q3	31.028.948	28.430.643
2011-Q4	---------	27.295.707
2012 GDP	---------	**111.233.502**
2011-Q1	---------	26.813.588
2011-Q2	---------	28.153.427
2011-Q3	---------	28.500.755
2011-Q4	---------	27.765.733

5. CONCLUSIONS

Gross Domestic Product is an important indicator for all economic units including companies, investors and households. Because it determines their future incomes, returns of their investments, cost of capital and so on. So economic units make their decisions and set economic policies depending on future economic conditions determined by what the future GDP will be. Here the question is which methods can be more suitable and successful in forecasting GDP. In this paper we applied Artificial Neural Networks method as a prediction model. Results suggest that forecasting performance of this variable can be improved using neural network models.

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