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A COMPARISON OF ARTIFICIAL NEURAL NETWORKS' AND ARIMA MODELS' SUCCESS IN GDP FORECAST

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Abstract

In this article, Artificial Neural Network's and ARIMA Model's success in GDP forecast and modelling is compared. Study is accomplished on the Turkish economy and the data used comprise the time period from the first quarter of 1987 to the third quarter of 2007. MAE, MSE, RMSE, and Theil-U criterias are used in the comparison of both models. The model that has these criterias low is superior to the other model. In this context, results obtained revealed that ARIMA model is superior to ANN model in GDP forecasting.

Key Words*: ARIMA, Artificial Neural Networks, Forecasting, GDP*

YAPAY SİNİR AĞI VE ARIMA MODELLERİNİN GSYİH TAHMİNİNDEKİ BAŞARISININ KARŞILAŞTIRILMASI

Özet

Bu makalede, GSYİH'nin tahmininde ve modellenmesinde yapay sinir ağı (YSA) modeli ile ARIMA modelinin başarısı karşılaştırılmaktadır. Çalışma Türkiye ekonomisi üzerine yapılmış ve 1987:Q1-2007:Q3 dönemini kapsayan veriler kullanılmıştır. Her iki modelin karşılaştırılmasında MAE, MSE, RMSE ve Theil-U kriterlerinden faydalanılmıştır. Bu kriterlerin daha düşük olduğu model, diğerine göre üstün olmaktadır. Bu bağlamda elde edilen sonuçlara göre, GSYİH'nin tahmininde ARIMA modeli YSA modelinden daha üstündür.

Anahtar Kelimeler: *ARIMA, Artificial Neural Networks, Forecasting, GDP*

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1. Introduction

In economic analysis, traditional models are mostly used for modelling of economic systems. Although supported by modern computers and methods, models are not able to give enough and correct information in explaining the economical abnormalities. Particularly frequent economic crisis increase the concern in forecasting of economy and modelling of macroeconomic structure. One of the most important factors in modelling of macroeconomy is to forecast of GDP and modelling GDP correctly. When GDP is modelled correctly, parameters like unemployment, exporting, importing, consumption can be adequately forecasted and political (solutions) can be developed. For this reason forecasting and modelling of GDP is very important.

Autoregressive integrated moving average (ARIMA), developed by Box-Jenkins, is applied successfully to economical time serial forecast and macroeconomy modelling. Similarly, the appearance of various neural network topologies and active learning algorithms enables successful forecasting. Although, artificial neural network applications are mostly encountered in economic literature, particularly in financial statistics and exchange rate domains, it is rare to come across ANN applications in macroeconomic time series. This study has importance in terms of its contribution to the economic literature.

In this study, the comparison of “neural network model and single variable autoregressive model performance on Turkey GDP’s forecasting and modelling is presented. In other words, the usability of neural network model in GDP forecasting is investigated. The aim is to determine which method is more succcessful. ARIMA models are modelled as the combination of past errors and past values of taken up time series. On the other hand, ANN can be succesfully applied on wide sized and complex modelling of irregular, irrational, stocasthic, non-linear, and time variable systems.[2]

The study actually has three parts. In the first part, the literature related to the subject is written, in the second part theoretical background of ANN and ARIMA is taken up. In the third and last part, the data set is introduced and application results are evaluated.

2. Literature

The artificial neural network applications in economical variables are relatively new. Kuan and White (1994)3, theoretically showed the usability of neural networks in economic variables beside the usability of traditional models and they emphasize the similarities of two methods. Afterwards, neural networks that are exposed theoretically are applied on various economical variables by many authors. Maaoumi, Khontanzad and Abaye (1994)[4], showed that 14 different macroeconomic series to be modelled and

[2] Y. Li et.al., “Macroeconomics Modelling on UK GDP Growth by Neural Computing”, Technical Report CSC-95009, 1995.
[3] C. M. Kuan - H. White, “Artifical Neural Networks: An Econometric Perspective”, Econometric Reviews, Vol. 13, 1994, pp. 1-91.
[4] E. Maaoumi et.al., “Artifical Neural Networks for Some Macroeconomic Series: A First Report”, Econometric Reviews, Vol. 13, 1994, pp. 105-122.

forecasted better with ANN. Swanson and White (1997)[5], have investigated the use of neural networks in forecasting of macroeconomical variables. They compared different linear and nonlinear models by using a large sample size. Thier findings indicated that marginal performance of multivariate linear models were better. Kohzadi et.al. (1995)[6], compared ANN and ARIMA, in the forecasting of Egypt's cereal future and they found out that aproximate error of neural network model is between %18 and %40 and they showed that this values were lower than the values gathered from ARIMA.

Tkacz and Hu (1999)[7], studied on whether ANN can be used in the modelling of output increase based on monetary and financial variables. According to the authors, ANN's forecasting performances were better than that of gathered from linear models. Li et.al. (1995)8 has modelled British GDP with artificial neural network. They compared the use of two different training algorithms based on neural network model.

Tkacz (2001)[9], carried out GDP forecasting of Canadian economy by using monetary and financial variables. In his study, author compared time series models (ARIMA, exponential smoothing), linear models and artificial neural network models. Their results indicated that the error values of ANN model were lower than error values of other models especially in long lasted GDP forecastings. In other words, ANN's forecasting performance is higher.

Junoh (2004)10, forecasted GDP of Malaysian economy by using information based economical indicators. In this study, author compared ANN and econometric approaches and showed that ANN had better results in GDP forecasting. Zhang (2003)[11], used hybrid approach that is the combination of ARIMA models and ANN models and the author obtained better results with hybrid approach.

As it is understood from the literature, there are a lot of studies about the comparison of ANN and other econometric methods', especially ARIMA in terms of their performances. However, there is no certain judgement about which one of these studies is superior to others.

[5] N. R. Swanson - H. White, "A Model Selection Approach to Real-Time Macroeconomic Forecasting Using Linear Models and Artificial Neural Networks", Review of Economics and Statistics, Vol. 79, pp. 540-550.

[6] N. Kohzadi et.al.,"Neural Networks for Forecasting: An Introduction", Canadian Journal of Agricultural Economics, Vol. 43, 1995, pp. 463-474.

[7] G. Tkacz - S. Hu, "Forecasting GDP Growth Using Artifical Neural Networks", Working Paper 1999-3 / Bank of Canada, 1999, pp. 1-24.

8 Li et.al., a.g.m.

[9] G. Tkacz, "Neural Network Forecasting of Canadian GDP Growth", International Journal of Forecasting, Vol. 17, 2001, pp. 57-69.

[10] M. Z. H. M. Junoh, "Predicting GDP Growth in Malaysia Using Knowledge-Based Economy Indicators: A Comparison Between Neural Network and Econometric Approach", Sunway College Journal, Vol. 1, 2004, pp. 39-50.

[11] G. P. Zhang, "Time Series Forecasting Using A Hybrid ARIMA and Neural Network Model", Neurocomputing, Vol. 50, 2003, pp.159-175.

3. Data and Methodology

3.1. Data

The data used in this study contain three month periods and comprise from the first quarter of 1987 to third quarter of 2007. Used data obtained from TCMB's electronic data distribution system[12] has been calculated with 1987's fixed prices. The data are used after purified from seasonability, since these data has seasonal characteristic. GDP variable, which is obtained based on expenditure approach, was used as output variable in ANN model while variables include private final consumption expenditure, government final consumption expenditure, gross domestic fixed capital formation, export of goods and services, and import of goods and services were used as input variables.

3.2. Methodology

In this part, models that are used in GDP forecasting are showed theoretically. Artificial neural network model and ARIMA model are analysed comparatively.

3.2.1. Artificial Neural Network

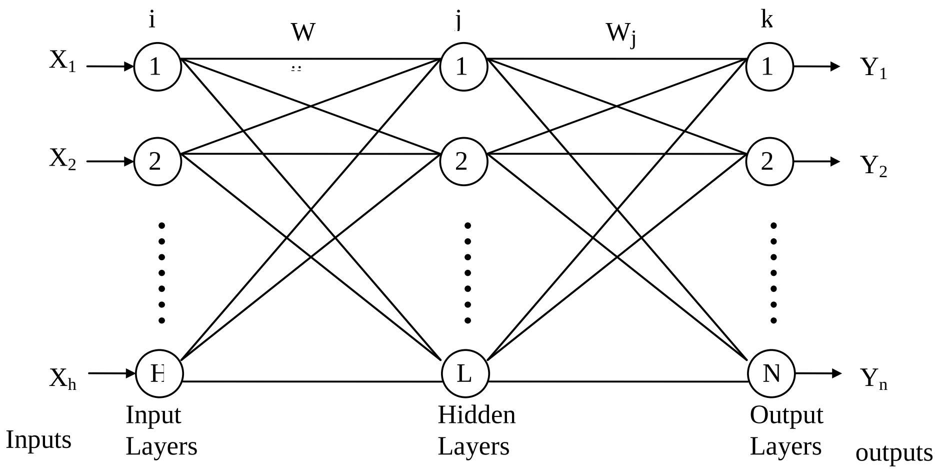
With the help of later developments in computer technology, intensive calculating methods like artificial neural network has gained importance and has gone to the fore as non-linear process catching method in complex data sets. This model provides an opportunity to model the relationship between one or more input (independent) variables and one or more output (dependent) variables. However, the relationship between input and output can not be always direct. This situation could be seen in the relationship between inflation and interest rates. It should be taken into account that there would be a number of possible transient variables including from interest rate change to inflation rate. Interest rates firstly affect durable consumption, investment, output and then effect inflation. Neural network models can catch these middle phases by the help of black box. In the black box, the heaviness between input variables and middle variables and as well as the heaviness between middle variables and output variables are calculated. Generally unknown middle variables are called as hidden units. Briefly, input information and output information corresponding to those input information are entered to the neural network and provided to learn the relationship between input and output and thus training of network is realised. Finally, true and the closest to real forecasting calculations are ordered from trained network.

There are many different neural network structures. Before entering training process, structure of neural network should be defined. Best structure of neural network is dependent on the type of data and system to be modelled. Furthermore, activation rules and learning mechanizm are effective in determination of the structure of neural network. One of the best known structures is backpropagation mechanizm based on multiplayer neural network model. Backpropagated and 3 layered neural network model is shown in Shape

[12] Variables and Codes: Private final consumption expenditure: TP.UR.G01; Government final consumption expenditure: TP.UR.G08; Gross domestic fixed capital formation: TP.UR.G11; Export of goods and services: TP.UR.G21; Import of goods and services: TP.UR.G22; GDP: TP.UR.G23. www.tcmb.gov.tr.

3.1.13 In the essence of feedback technique, arrangement of heaviness to backwards lies on to minimise the error that occurred in output layer.14

Shape 3.1: A three-layer ANN Architecture.



In the figure above, X1, X2 .... Xn are input variables; Y1, Y2.....Yn are output variables; Wi and Wj are heaviness and j is the number of hidden units.

3.2.2. ARIMA

Box-Jenkins ARIMA linear models have been used in many field of time series in forecasting for more than half of century. This method, which is an analysing and forecasting method in time series, is based on linear and stochastic processes. Box-Jenkins forecasting methods are these: Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA).15

ARMA models, being as a stationary stochastic process, are linear function of past observations and past error terms of variable used in analysis. However, time series do not have stationary process property everytime. Generally differentation of 1st and 2nd series are taken to make stationary from a non-stationary time series.

[13] Li et.al., a.g.m.

[14] S. Haykin, **Neural Networks: A Comprehensive Foundation,** New Jersey, Perenctice Hall, 1999, pp.185.

[15] J. M. R. Poo, Computer-Aided Introduction to Econometrics, 2003.

Box-Jenkins (1976)[16] defines ARIMA models as integrated models. In other words, models applied on although being non-stationary, becoming stationary series by taking difference, are defined as non-stationary linear stochastic models. In fact these models are ARIMA (p, d, q) models which are the combination of AR and MA models in which the difference was taken for d times. Both seasonal and non-seasonal time series are modelled with the combination of past values and past errors, showed as ARIMA (p, d, q) and expressed as below.[17]

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + ... + \phi_p X_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - ....\theta_q e_{t-q}$$

ϕ_1, ϕ_2 …..in Equation 1 are coefficients. p and q are degrees of autoregressive and moving average polinoms, respectively. There are basicly three stages in this technique namely model defining, parameter forecasting and control testing.

4. Findings

4.1. Findings Related to ANN

Analysis of ANN is composed of two phase and these are training and test phases. Model education is quite important in neural network analysis because if the model is not trained well in macroeconomic variable, true and close forecasting could not be achieved in the process of testing. For this reason, numbers of hidden layer and hidden units are very important in feedback neural network model. Moreover, there are two factors that should be determined during the training process. The first one is training momentum and second one is learning rate. Additional information about the structure of neural network and other components that are important in this structure can be acquaired from Haykin (1999).

A feedback technique was used in this study. ANN was trained by using Levenberg-Marquardt (LM) method and benefited from logarithm sigmoid function as the transfer function. Because the LM method is faster and more powerful than the traditional gradient descent method.18 The first thing to be done in data processing is to eliminate residuals in the data. To do this, the data used in the study were normalized in the 0,2-0,8 interval. Different numbers of hidden units were used to increase ANN performance and the best number of hidden unit was determined as two. Similarly, determination of best iteration number also affect the ANN performance. In this respect alternative iteration numbers were tested and 13 is found as the best iteration number. MATLAB 7.01 software is used in ANN analysis.

[16] G. E. P. Box - G. M. Jenkins, Time Series Analysis: Forecasting and Control, Holdan–Day, 1976

[17] S. L. Ho et.al., "A Comparative Study of Neural Network and Box-Jenkins ARIMA Modeling in Time Series Prediction", Computers & Industrial Engineering, Vol. 42, 2002, pp. 371-375.

[18] M. T. Hagan - M. B. Menhaj, "Training feed forward networks with the Marquaradt algorithm", IEEE Trans Neural Networks, 1994, Vol. 6, pp. 861–7; Özgür Kisi, "Streamflow forecasting using different artificial neural network algorithms", ASCE J. of Hydrol. Eng., Vol. 12, No. 5, 2007, pp. 532-539.

4.2. Findings Related to ARIMA

In the determination of ARIMA models, variable's autocorrelation and partial autocorrelation functions are used. The residuals will be helpful to obtain best ARIMA structure. The most appropriate model was tried to be obtained by the help of data between 1987:Q1-2002:Q4. In the scope of determined model/s, GDP forecasting belonging to 2003:Q1- 2007: Q3 years, is accomplished. In the application, it is benefited from Eviews 5.1 software.

Series' stationary should be known in ARIMA models that will be put into practice. For this reason, unit root investigation of series was carried out by using ADF test. ADF results belonging to GDP series is given in Table 4.1. ADF test is a unilateral test and Mac Kinnon critical value always takes negative value. Besides, calculated DF/ADF values should be absolutely bigger than Mac Kinnon critical value. In this respect, it is understood that the first difference of GDP variable is stationary.

Table 4.1: ADF unit root test results

	Level			**First Difference**		
	None	**Intercept**	**Trend and intercept**	**None**	**Intercept**	**Trend and intercept**
GDP	1,28(0)* [-2,60]**	-1,39(0) [-3,53]	-3,65(0) [-4,11]	-8,31(0) [-2,60]	-8,55(1) [-3,54]	-8,49(1) [-4,11]

Note: *Values in parenthesis display lag number selected by SC criterion.

** Mac Kinnon test critical values % 1 level.

AIC and SC were used to obtain best ARIMA structure. Autocorrelation that belongs to GDP variable and partial autocorrelation values were examined and alternative models were experimented. In the scope of obtained results, it could be concluded that ARIMA (2, 1, 2) structure was the best ARIMA model. ACF and PACF values of acquired residuals from ARIMA (2, 1, 2) model were desired values and they did not have any residuals.

Table 4.2: ARIMA results that are related to GDP

Variable	**coefficient**	**t statistic**	**Probability**
C	17069	1.541	0.128
AR(2)	-0.918	-10.501	0.000
MA(2)	0.751	5.444	0.000
Adjusted R2	0.176	**Prob(F-statistic)**	0.001
F-statistic	7.437		

In Table 4.2, most suitable ARIMA (2, 1, 2) model is placed. As it is seen from the table, all coefficients are meaningful in the %1 level. This model structure has been used in testing phase of ARIMA forecasting.

4.3. Comparison of ANN and ARIMA Findings

Some criteria, based on the deviation between real value and forecast value, are developed to compare the foreseeing success of the applied models. Equations for the success criteria are given below:

$$\mathrm{MAE} = \frac{\sum |A_t - F_t|}{n}, \quad \mathrm{MSE} = \frac{\sum (A_t - F_t)^2}{n}, \quad \mathrm{RMSE} = \sqrt{\frac{\sum (A_t - F_t)^2}{n}}, \quad \mathrm{U} = \frac{RMSE^2}{(\sum A_t^2)/n}$$

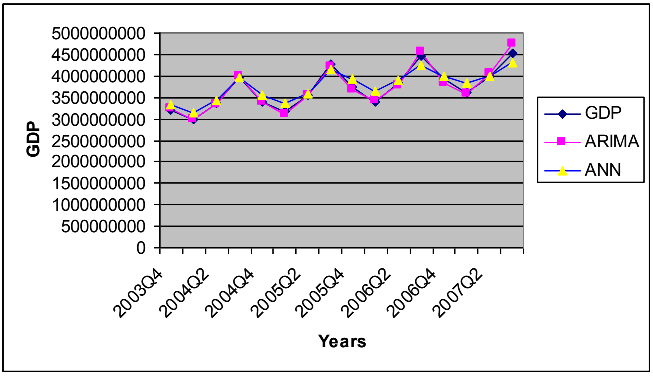
MAE, MSE, RMSE, and U abbreviations mean that: Mean Absolute Error, Mean Square Error, Root Mean Squar Error, and Theil-U coefficient, respectively. The technique with a low success criteria has a better forecasting performance.

Table 4.3: ANN performance that correspond ARIMA model

Performance Criterions	ANN	ARIMA
RMSE	156900066	66036795
MSE	2.46176E+16	4.36086E+15
MAE	133408564	48894195
Theil-U	0.00175	0.00031

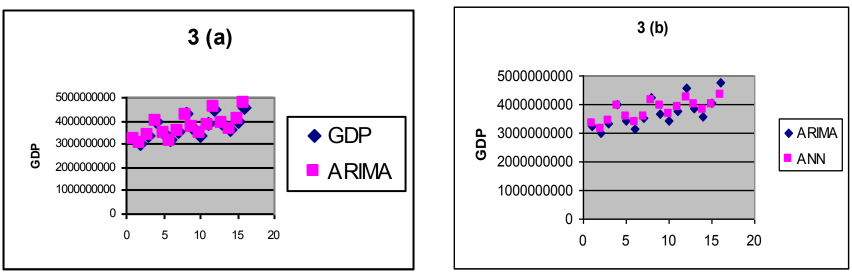
Forecasting performances of ANN and ARIMA models are illustrated on Table 4.3. According to the Table 4.3, the error values of ANN are higher than those of ARIMA for all criteria. In this respect, the ARIMA model, which uses standardized statistical measurement methods, has reached higher performance compared to the ANN model. In other words, results from the ARIMA model are better than the results of the ANN model.

Figure 4.1: GDP forecast



Real and forecasted values about GDP are placed on Figure 4.1. According to the figure, forecasted values obtained from ARIMA model are very close to real values of GDP and also show the same trend during the whole period of time analyzed. Similar situation could be seen on the scattered dispersion placed on Figure 4.2 (a) and 4.2 (b). Forecasted values obtained by ARIMA model are almost same with real values.

Figure 4.2: (a) GDP forecast with ARIMA; (b) GDP forecast with ANN



5. Results

In this study, comparison of neural network model and variable autoregressive models' modelling and forecasting performances in Turkish GDP is presented. In neural network model, multiplayer neural network based on feedback training mechanism was used. Feedback mechanizm is a classical optimization technique. ARIMA is composed of the combination of past values and past errors of time series analyzed. Variables used in the study in which data are calculated according to 1987 year prices are GDP and components of GDP.

Studies related to application of ANN to macroeconomic time series are very limited. The results obtained from these studies can not put forward clear information. While some studies express superiority of ANN, other studies point out weakness of ANN. The results obtained from this study revealed that ARIMA model using standardized statistical measurement criterion has reached higher performance than artificial neural network. In other words, results obtained from ARIMA model was better than results of ANN model. This study has importance due to its contribution to the literature. Besides, being one of the first studies about Turkish economy make this study and its findings important.

6. References

BOX, G. E. P. – JENKINS, G. M., **Time Series Analysis: Forecasting and Control**, Holdan–Day, 1976.

HAGAN, M. T. - MENHAJ, M. B., "Training feed forward networks with the Marquaradt algorithm", **IEEE Trans Neural Networks**, 1994, Vol. 6, pp. 861–867.

HAYKIN, S., **Neural Networks: A Comprehensive Foundation,** New Jersey Perenctice Hall, 1999.

HO, S. L., et.al., "A Comparative Study of Neural Network and Box-Jenkins ARIMA Modeling in Time Series Prediction", **Computers & Industrial Engineering**, Vol. 42, 2002, pp. 371-375.

JUNOH, M. Z. H. M., "Predicting GDP Growth in Malaysia Using Knowledge-Based Economy Indicators: A Comparison Between Neural Network and Econometric Approach", **Sunway College Journal**, Vol. 1, 2004, pp. 39-50.

KİSİ, Ö., "Streamflow forecasting using different artificial neural network algorithms", **ASCE J. of Hydrol. Eng.**, Vol. 12, No. 5, 2007, pp. 532-539.

KOHZADI, N., et.al., "Neural Networks for Forecasting: An Introduction", **Canadian Journal of Agricultural Economics,** Vol. 43, 1995, pp. 463-474.

KUAN, C. M – WHITE, H., "Artifical Neural Networks: An Econometric Perspective", **Econometric Reviews**, Vol. 13, 1994, pp. 1-91

LI, Y., et.al., "Macroeconomics Modelling on UK GDP Growth by Neural Computing", **Technical Report CSC-95009**, 1995.

MAAOUMI, E., et.al., "Artifical Neural Networks for Some Macroeconomic Series: A First Report", **Econometric Reviews**, Vol. 13, 1994, pp. 105-122.

NAKAMURA, E., "Inflation Forecasting Using a Neural Network", **Economics Letters**, Vol. 86, 2005, pp. 373-378.

POO, J. M. R., **Computer-Aided Introduction to Econometrics**, 2003.

TKACZ, G., "Non-Parametric and Neural Network Models of Inflation Changes", **Working Paper 2000-7 / Bank of Canada**, 2000, pp. 1-18.

TKACZ, G., "Neural Network Forecasting of Canadian GDP Growth", **International Journal of Forecasting**, Vol. 17, 2001, pp. 57-69.

TKACZ, G. – HU, S., "Forecasting GDP Growth Using Artifical Neural Networks", **Working Paper 1999-3 / Bank of Canada**, 1999, pp. 1-24.

SWANSON, N. R. – WHITE, H., "A Model Selection Approach to Real-Time Macroeconomic Forecasting Using Linear Models and Artificial Neural Networks", **Review of Economics and Statistics**, Vol. 79, pp. 540-550.

ZHANG, G. P., "Time Series Forecasting Using A Hybrid ARIMA and Neural Network Model", **Neurocomputing**, Vol. 50, 2003, pp.159-175.