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Scientific Annals of Economics and Business
65 (2), 2018, 159-169
DOI: 10.2478/saeb-2018-0010

Comparing Simple Forecasting Methods and Complex Methods: A Frame of Forecasting Competition

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Abstract

The gross capital formation (GCF), which helps to gradually increase GDP itself, is financed by domestic savings (DS) in both developed and developing countries. Therefore, forecasting GCF is the key subject to the economists' decisions making. In this study, I use simple forecasting methods, namely dynamic relation model called "Autoregressive Distributed Lag Model (ARDL)", and complex methods such as Adaptive Neuro Fuzzy Inference System (ANFIS) method and ARIMA-ANFIS method to determine which method provides better out-of-sample forecasting performance. In addition, the contribution of this study is to show how important to use domestic savings in forecasting GCF. On the other hand, ANFIS and hybrid ARIMA-ANFIS methods are comparatively new, and no GCF modeling using ANFIS and ARIMA-ANFIS was attempted until recently to the best of my knowledge. In addition, Autoregressive Integrated Moving Average (ARIMA) method and Vector Autoregressive (VAR) model serve as benchmarks, allowing for fair competing for the study.

Keywords: dynamic relation model; ANFIS; ARIMA-ANFIS; gross capital formation; domestic savings.

JEL classification: C45; C53.

1. INTRODUCTION

The starting idea of this paper is to reveal whether the impact of domestic saving on GCF helps to obtain more accurate forecasts of GCF itself. As is known, some variables can be forecasted by their lagged values. In literature, Vector Autoregressive (VAR) models are very popular tools for forecasting. Firstly, VAR model is introduced by Sims (1980) as an alternative approach to macroeconometric models. In VAR model, dependent variable is explained by past values of dependent and independent variables. The lag order in the model is decided by the information criterion such as Akaike information criterion (AIC) or Schwarz information criterion (SIC). In VAR model, the variables must be stationary. If the variables are not stationary, this condition causes some flaws on the nature of dynamic relationship because of taking difference for each variable in dataset. Depending on this particular issue in hand, cointegration techniques can be employed to overcome this

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problem. The first cointegration concept is introduced by Granger (1981). The development of this concept shows the following pattern: i) Engle and Yoo (1987); ii) Johansen (1995) and iii) the other techniques such as ARDL. In the context of cointegration analysis, the variables in the model should not be stationary, and they must be integrated to the same order except ARDL model. Therefore, taking difference of the variables is no need anymore. For this reason, cointegration techniques prevent the nature of dynamic relationship breakdown. However, having or not having the nature of dynamic relationship can make the difference in estimation of model parameters but forecasting the model. Therefore, VAR model can produce more accurate forecasts than the cointegration model.

That kind of economic time series forecasting is generally hard enough and also challenging task for researchers because of the complex structure of economic series. Forecasting methods, namely classical models (such as ARIMA, regression model, exponential smoothing, etc.) and the AI methods (such as artificial neural network (ANN), ANFIS, etc.) are proposed in the literature. In recent years, ANFIS and hybrid methods have become popular for forecasting in a large number of areas. As a result, ANFIS and ARIMA-ANFIS method have been chosen to make comparisons for forecasting purpose. A better understanding of power of simple forecasting and complex methods is very important. For this purpose and in order to have a fair competition, I also use some classical econometrics forecasting methods such as ARIMA and VAR.

This paper is organized as follows: Following with an introduction in Section 1, I present the literature in Section 2. Section 3 discusses the methodology and datasets. In Section 4, I present the analysis results. In Section 5, conclusions are listed.

2. LITERATURE

This section presents relevant research with a thematic review of the forecasting literature. There are several ways for forecasting data, and it can be carried out either with one or several predictors. The univariate methods usually employed in the field of forecasting are VAR and Box-Jenkins (ARIMA) methods. These methods are very popular because of their simplicity and ease of application for practitioners and researchers.

The outcome of the study by Reid (1971) showed that when ARIMA model is compared to the exponential soothing or step-wise regression, ARIMA model has more accurate results. Nelson (1972) stated that using ARMA models give more robust forecasts than complex econometric models in terms of post sample period. Newbold and Granger (1974) concluded from their study that the results of ARIMA models are better than exponential smoothing model. Claycombe and Sullivan (1977) found that if annual data is used in the analysis, the double exponential smoothing method comes first and the Winter's method comes second with regard to minimum mean square error (MSE). However, if quarterly data is used in the analysis, the result is exactly reverse. Larson (1983) indicated that the out-of-sample forecasts of simple models, namely ARIMA and VAR model, are relatively good. Sabur and Haque (1993) emphasized that ARIMA model should be used only for short-term forecasts.

Engle and Yoo (1987) compared unrestricted vector autoregression model with error-correction model. They deduced from their study that error-correction model performs better forecasting performance in the long-run, but not in the short-run. Hall *et al.* (1992) employed theoretical error-correction, levels VAR, and naïve models to obtain one-step-ahead forecasts. They reported that the error-correction model improves forecasting performance. Another study was explained by Fanchon and Wendel (1992), who argued the forecasting performances of levels VAR, Bayesian VAR, and error correction models. They showed that the VAR in levels model produce the best forecasts.

Kaur *et al.* (2010) compared the different forecasting methods such as ANN and ANFIS. They indicated that ANFIS method gives more accurate results. Hernandez *et al.* (2010) found that ARIMA model is better than ANFIS method in terms of their comparison result based on root mean square error (RMSE). Yayar *et al.* (2011) stated that ANFIS method has better forecasting performance than ARIMA model by using energy consumption data. Rahman *et al.* (2013) clarified that ARIMA is preferable over ANFIS method. However, Tektas (2010) found that ANFIS method is better approach than ARIMA.

3. METHODOLOGY AND DATA

This part is divided into two parts. The first part consists of methodology, whereas the second part introduces the dataset.

3.1 An Overview of Forecasting Methods

3.1.1 ARDL Approach

The ARDL bound test is introduced by Pesaran and Shin (1999). It is the most useful approach for determining the existence of cointegration in small samples. One of the advantages of the ARDL approach is that it can be applied whether all variables in the model are purely of I(1) or purely I(0) or a mixture of both. The second advantage of the ARDL bound test is that if a researcher or practitioner is unsure of the unit root properties of the data, the ARDL approach is the most effective model for empirical work. The ARDL model can be presented as follows (Mallick and Agarwal, 2005):

$$\Phi(L,p)y_t = \alpha_0 + \sum_{i=1}^{k} \beta_i (L,q_i) x_{it} + u_t \quad (1)$$

where,

$$\Phi(L,p) = 1 - \Phi_1 L^1 - \Phi_2 L^2 + \ldots\ldots - \Phi_p L^p \quad (2)$$

$$\beta_i (L,q_i) = \beta_0 L^0 + \beta_{i1} L^1 + \beta_{i2} L^2 + \ldots\ldots + \beta_{iq} L^q, \quad i=1,2,\ldots,k, \quad (3)$$

In Equation (1), α_0 is constant, y_t is dependent variable, x_t is independent variable and L is the lag operator respectively.

$$y_t = \mu + \sum_{i=1}^{k} \beta_i x_{it} + \varepsilon_t \quad (4)$$

The coefficients which represent a long-term relationship are given as follows:

$$\hat{\mu} = \frac{\alpha_0}{1 - (\Phi_1 + \Phi_2 + \ldots + \Phi_p)} \quad (5)$$

$$\hat{\beta} = \frac{\beta_{i0}+\beta_{i1}+\beta_{i2}+\ldots+\beta_{iq}}{1-(\Phi_1+\Phi_2+\ldots+\Phi_q)}, \qquad i=1,2,\ldots k \tag{6}$$

The Vector Error Correction Model (VECM) which allows short-run dynamic between variables is presented below.

$$\begin{aligned}\Delta Y_t &= \alpha_0+\sum_{i=1}^{k}\beta_{i1}\Delta X_{it}-\sum_{i=1}^{\hat{p}-1}\Phi_{i1}\Delta y_{t-j}-\sum_{i=1}^{k}\sum_{i=1}^{\hat{q}-1}\beta_{ij}\Delta X_{it-j} \\ &= -\Phi(1,\hat{p})ECM_{t-1}+u_t\end{aligned} \tag{7}$$

$$ECM_{t-1} = y_t-\sum_{i=1}^{k}\hat{\beta}_i\Delta X_{it} \tag{8}$$

where ECM_{t-1} is an error correction term. The error correction $\Phi(1,\hat{p})$ term indicates the speed of adjustment to the equilibrium level after a shock. Theoretically, the sign of error correction term should be negative and significant.

3.1.2 ANFIS Method

This method based on the theory of fuzzy set and fuzzy logic is proposed by Jang (1993). This method is composed of ANN system and FIS system. ANN is known as statistical data modelling tool. It refers to learning algorithm which can capture the complex patterns in the relationship between input and output data. The FIS comprises membership function, fuzzy logic operator and if-then rules. Figure no. 1 shows the ANFIS architecture.

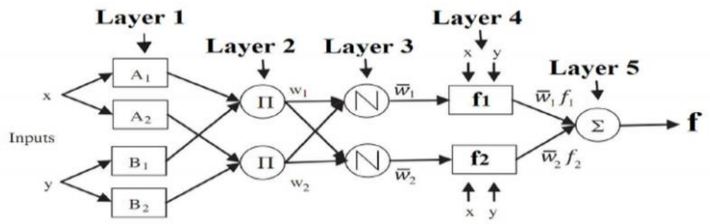

Figure no. 1 – An ANFIS Architecture for a two rule Sugeno System

As a matter of fact, numerous different types of FIS have been proposed in the literature such as Mamdani, Sugeno and etc. (Sugeno and Kang, 1988). The Sugeno model becomes the most proper model in the usage of ANFIS method for economic predictions. The Sugeno model assumes that rule outputs are represented by linear combination of input variables and a constant term. The term of linear combination is very important in terms of the consistency of the study result since ARDL cointegration technique is a linear approach.

3.1.3 ARIMA Method

ARIMA models, which include autoregressive polynomial (AR), an order of integration, and moving average polynomial (MA), are appropriate for modelling univariate time series. The point is that ARIMA models are constructed with objectives in mind: to forecast GCF series and to serve as benchmark for the forecasts obtained from the other individual models. ARIMA models are also known as Box and Jenkins models. Therefore, in this study, the following steps of Box and Jenkins' method are followed; that is:

- Identification
- Estimation
- Diagnostic Checking
- Model's use

3.1.4 VAR Method

In practice, VAR models are used as linear forecasting models in empirical macroeconomic researches. Unlike ARIMA models, VAR models are considered as not only time series modes such as ARIMA models as well as incorporating theoretical considerations but also structural models. A *K* dimensional VAR(p) model is defined as follows:

$$y_t = (y_{1t}, \ldots, y_{kt}, \ldots, y_{Kt}) \ \ for \ \ k = 1, \ldots, K \tag{9}$$

$$y_t = \Phi_1 y_{t-1} + \ldots + \Phi_p y_{t-p} + u_t \tag{10}$$

where Φ_i are $(K \times K)$ coefficient matrices for $i = 1 \ldots, p$ and u_t is K dimensional white noise. In the context of the study, we follow the three 3 steps in VAR model:

- Model Selection (identify the order p)
- Estimating the Parameters
- Testing the Residuals for White Noise.

3.2 Datasets

The dataset from Turkey used in this study consists of the ratio of investment to GDP and the ratio of domestic saving to GDP covering the period between 1960 and 2017. Both data are obtained from https://data.worldbank.org. Investment is Gross Capital Formation. Descriptive statistics for the time series used in the analysis are summarized in Table no. 1.

Table no 1 – Descriptive Statistics

	GCF	DS
Mean	20.51474	17.52354
Median	21.24316	19.3039
Maximum	31.26869	26.24371
Minimum	9.972299	8.310249
Standard deviation	6.098794	5.727512
Skewness	-0.08108	-0.07864
Kurtosis	1.81559	1.460958
Jarque-Bera	3.394162	5.684292
Probability	0.183218	0.0583
Observations	57	57

According to Table no. 1, the distribution of GCF and DS series is said to be left-skewed and the dataset has lighter tail than normal because the kurtosis is less than three. Table no. 1 also clearly shows that the dataset seems normally distributed.

The most common test for determining the order of integration is the Augmented Dickey-Fuller test (ADF) introduced by Dickey and Fuller (1979). An alternative to the ADF test is the Phillips-Perron (PP) test introduced by Phillips and Perron (1988) that offers a method of correcting for serial correlation in a unit root test. In the present study, I use both the ADF and PP unit root tests. Table no. 2 reports the results of the ADF and PP tests for the variables GCF and DS. In the light of the results obtained from Table no. 2, ARDL approach can be employed for the dataset.

Table no. 2 – Unit Root Tests

Variables		**ADF Test – Level**		**ADF Test-First Difference**	
		Intercept	Intercept & Trend	Intercept	Intercept & Trend
GCF		-1.758(0)	-4.283(1)*	-9.657(0)*	–
DS		-1.359(0)	-3.307(0)	-6.953(1) *	-6.892(0)*
Significance Level	*1%	-3.552	-4.130	-3.552	-4.130
	**5%	-2.914	-3.492	-2.914	-3.492
	***10%	-2.595	-3.174	-2.595	-3.174
Variables		**PP Test-Level**		**PP Test-First Difference**	
		Intercept	Intercept & Trend	Intercept	Intercept & Trend
GCF		-1.541(3)	-4.267(1)*	-11.484(7)*	–
DS		-1.031(14)	-3.218(5) ***	-11.615(28)*	-12.072(29) *
Significance Level	*1%	-3.552	-4.130	-3.552	-4.130
	**5%	-2.914	-3.492	-2.914	-3.492
	***10%	-2.595	-3.174	-2.595	-3.174

Note: GCF variable is not stationary in intercept model but stationary in trend & intercept model. DS variable is not stationary in both intercept and intercept & trend model.

4. EMPIRICAL RESULTS

4.1 Results Based on ARDL Approach

In order for a model to be used for forecasting purpose, I divide the dataset into two parts. The first part is called "training set' and the second part is called "test set". Depending our dataset size, the dataset is splitted into training and test set using 70%-30% of original dataset. The idea is that more training data is a good thing, and is a way of counteracting over-fitting. To this end, the training set includes 41 observations, and the test set includes 16 observations.

The first step in the analysis is to evaluate whether there is a long-run relationship between GCF and DS. The results are given in Table no. 3 and Table no. 4.

Table no. 3 – F-statistic for Testing the Existence of a Long-run Relationship

Test Statistics	Value	k
F-statistic	**8.487043**	1
Critical	Value	Bounds
Significance	I0 Bound	I1 Bound
10%	4.04	4.78
5%	4.94	5.73
2.50%	5.77	6.68
1%	6.84	7.84

As can be seen in Table no. 3, the computed F-statistic for one lag-length is higher than the upper bound. This result confirms that there is a long-run relationship between GCF and DS variables. The long-run coefficients and error correction model results are reported in Table no. 4 and Table no. 5 respectively.

Table no. 4 – Long-run ARDL (1,2) Model Estimates

Long -Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DS	0.959409	0.10149	9.453213	0.000
C	3.99984	1.623747	2.463339	0.019

Table no. 5 – Error Correction Model

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic
D(DS)	0.634792	0.147093	4.315572
D(DS(-1))	-0.312263	0.142268	-2.1949
ECM(-1)	-0.616159	0.14966	-4.11707
Cointeq =GCF -(0.9594*DS +3.9998)			

The results in Table no. 5 reveal that the coefficient of ECM(-1) is negative and statistically significant as expected. The ARDL(1,2) model is considered to be successful to satisfy the conditions for forecasting. Also, the results based on ARDL(1,4) with breakpoint are given in Annexes. There were some major crises in Turkey. The crisis of 1994 is one of them in training period. As is known, economic growth slowed down during 1994. Therefore, I use dummy variable to represent breakpoint in the model.

4.2 Results Based on ANFIS and ARIMA-ANFIS Method

To compare the obtained results of GCF forecasting by ARDL, I use ANFIS method. ANFIS method is applied by using the Matlab program. At first, I use one factor – the lagged values of GCF –as input for the forecasting GCF. Second, I use one factor –DS variable – as input for forecasting. The first 31 of data is used as training set to optimize the model parameters, 10 of data is used as validation set and the last 16 serves as the test set. The used steps are as follows:

Step 1: Define the lagged values of GCF and DS variable as the input variables and GCF as the output variable.

Step 2: Divide all data into three subsets. The first 31 observations are for training set, the next 10 observations are for validation set and the last 16 observations are for test set.

Step3: Determine the rules and membership functions by using genfis1 function.

Step4: Choose the best net based on the validation data by using anfis function.

Step5: Evaluate the chosen net based on test data by using evalfis function.

As seen in validation test results, if the input variable is DS series, I obtain better out-of-sample forecasting performance than the input to the first lagged value of GCF. Figures no. 2 and no. 3 shows the difference between inputs in terms of forecasting performance.

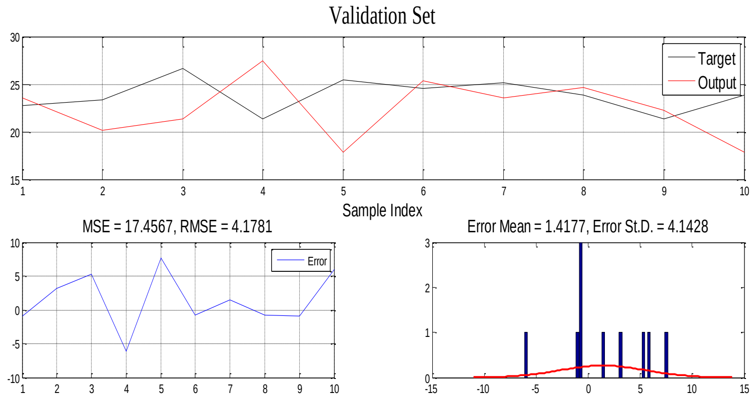

Figure no. 2 – Forecasting Performance when GFC is output and the first lagged value of GCF is input

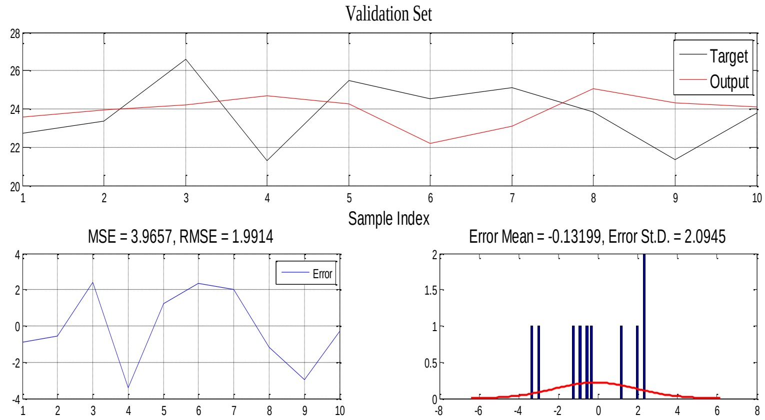

Figure no. 3 – Forecasting Performance when GFC is output and DS is input

After deciding input variable to be used in ANFIS method, I report out-of-sample forecasting results of ARDL and ANFIS methods. In ANFIS method, when DS series is used as input variable, I find better out-of-sample forecasting performance in validation set. Therefore, I use the same steps for the test set to obtain out-of-sample forecasts.

Table no. 6 – Out-of-sample Forecasting Performance

	RMSE	**MAE**
ARDL(1,2)	2.846	2.315
ARDL(1,4) with break	2.735	**2.018**
ANFIS	4.236	3.840
ARIMA-ANFIS	2.792	2.242
ARIMA(0,1,1)	**2.672**	2.127
VAR	2.699	2.161

Note: In ARIMA model, AIC criterion is used for determining the best ARIMA structure. In VAR model, lag is chosen as two by using AIC criterion.

In addition to ANFIS method, I use ARIMA-ANFIS hybrid method to check whether the more accurate forecasts can be obtained than ARIMA or ANFIS method. In ARIMA-

ANFIS method, the rules and membership functions are determined by genfis3 function. As is known, a time series is composed of linear and nonlinear component. Firstly, I estimate the linear component using ARIMA model. Second, the nonlinear component that corresponds to error term is estimated by ANFIS method. Comparisons of the models are given in Table no. 6. In addition, the plot of forecasting results is given in Figure no. 4.

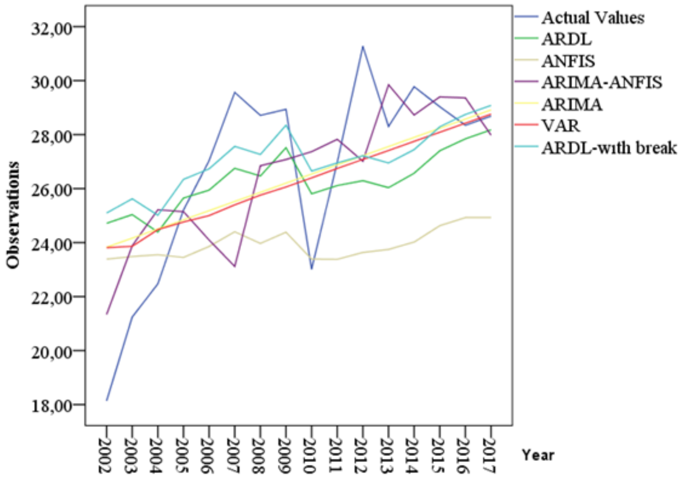

Figure no. 4 – Out-of-sample Forecasts

According to Figure no. 4, the forecasts generated by individual models show that ARDL-with break model leads to more accurate forecasts than the other models, because the forecasts by ARDL-with break model follow the pattern of actual data better than the other forecasts by the models used in this study. Based on the accuracy of MAE, the obtained result is proved by Figure no. 4.

5. CONCLUSIONS

Gross capital formation forecasting plays a key role in an economy of countries. In this paper, I use simple forecasting methods and complex ones to make comparison of methods in terms of out-of-sample forecasting. By considering forecasting performance measure, RMSE, ARIMA model shows better forecasting performance than the other methods. However, according to MAE measure, ARDL model with breakpoint gives better out-of-sample forecasting performance. This result is very important for future studies. If the breakpoint is added to the model, ARDL model improves the forecasting accuracy. Besides, this finding supports the studies which conclude that error-correction model improves forecasting performance in literature. The most important findings are that the results support the findings in the literature that domestic savings have very important role, in particular forecasting performance of the model, on gross capital formation; the results show that dynamic relation model is better than ANFIS and ARIMA-ANFIS method. From this, it can be concluded that computational complexity is not always a solution to obtain better forecasting performance. This finding is line with the other study by Hendry and Clements (2003) that found that the simple forecasting models perform the best.

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ANNEX 1

F-statistic for Testing the Existence of a Long-run Relationship

Test Statistics	Value	k
F-statistic	**7.651585**	1
Critical	Value	Bounds
Significance	I0 Bound	I1 Bound
10%	4.04	4.78
5%	4.94	5.73
2.50%	5.77	6.68
1%	6.84	7.84

ANNEX 2

Long-run ARDL(1,4) Model Estimates

Long -Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
DS	1.027	0.107	9.529	0.000
1994-break	-11.536	5.423	-2.127	0.038
C	3.352	1.990	1.684	0.099

ANNEX 3

Error Correction Model

Cointegrating Form				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(DS)	0.701	0.146	4.799	0.000
D(DS(-1))	-0.606	0.208	-2.916	0.005
D(DS(-2))	0.489	0.207	2.357	0.022
D(DS(-3))	-0.310	0.142	-2.176	0.034
1994-break	-5.414	1.927	-2.811	0.007
ECM(-1)	-0.469	0.120	-3.905	0.000
Cointeq =GCF -(1.0279*DS -11.536(1994-break)+3.353)				

Note: The results in reveal that the coefficient of ECM(-1) is negative and statistically significant as expected.

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