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Research Article

Estimating the macroeconomic ındicators using ARIMA and ANFIS methods

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ABSTRACT

In this paper, inflation rates were predicted by using the adaptive neuro fuzzy inference system (ANFIS) and auto regressive integrated moving average (ARIMA) method. This study was carried out to contribute to the inflation forecasting studies in the literature and to diversify the forecasting studies made with artificial neural networks and traditional forecasting methods for the time series. Variables consisted of money supply, exchange rates and interest rates used in ANFIS model has been chosen by a detailed literature review. The data of this article were obtained from the Central Bank of Republic of Turkey. Results obtained from established models and the real values were compared using the performance criteria of root mean square error (RMSE), coefficient of determination (R^2), mean absolute error (MAE) and symetric mean absolute percentage error (SMAPE). Result illustrates the success of the ANFIS to predict the inflation rate and ANFIS model outperforms ARIMA model.

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INTRODUCTION

One of the most common terms in economics is inflation. In its simplest definition, inflation means a continuous increase in the general level of prices. Individual price increases are not defined as inflation, that is, the general level of prices must be in a continuous increase [1]. As inflation rises, people can buy less and less products and services with the same amount of money. This means more money coming out of your pocket every time. Inflation can create some big problems at the societal level. In case of high inflation, the cost of goods and services increases as inflation increases for individuals with fixed income. This situation reduces the purchasing power of payroll employees. Therefore, it causes the income distribution to deteriorate to the detriment of fixed incomes [2].

According to the causes of inflation, it can be divided into two as cost-push inflation and demand-pull inflation [3]. Inflation can be caused by only one of these reasons, or it can occur with the effect of all of them. In the demand-pull inflation, by the increase in the money supply in the market, people demand more products because they will have more money in their hands. As long as the amount of production is not increased, the prices will increase because the amount of product will decrease. Since the application of lower interest rates than the market will accept will increase the money supply, low interest is considered as one of the causes of the demand inflation. Cost-push inflation results from high cost. The source of the cost increase is generally due to the exchange rate increases and the increase in energy and raw material prices. In order to reduce costs in supply inflation, employers may choose to lay off workers. This, in turn, leads to higher unemployment rates and less consumption by layoffs. Thus, the economy may enter the recession period. The coexistence of stagnation and inflation is called stagflation. Inflation can be

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divided into four as creeping inflation, walking inflation, galloping inflation and hyperinflation according to the rate of price increase. Less than 4% inflation defined as creeping inflation. If inflation between 4% and 10%, it is named as walking inflation whereas between 10% and 50% inflation named as galloping inflation. More than 50% inflation is defined as hyperinflation [4].

Measuring and predicting inflation enables the development of appropriate fiscal policies in order to determine the course of the economy and to reduce the rising inflation level [2]. Therefore, financial institutions and governments predict the inflation regularly. They shape their monetary policies according to the results of these predictions. For the forecasting of inflation, surveys are generally made or traditional statistical methods are used. However, in recent years, with the development of machine learning and their widespread utilization in different fields, such studies have begun to be made with artificial neural networks.

Inflation expectations influence financial markets. Inflation expectations affect monetary and fiscal policies of central banks. This situation affects the business decisions of the governments. Inflation anticipation also have an impact on the variety of business decisions, including the pricing of services, wages in labor contracts, corporate investment, financing decisions and firms' hedging decisions. Inflation expectations also affect banks' lending decisions. High inflation expectation increases the risks. All of these will affect the efficiency of the whole economy to some extent [5].

Use of computational intelligence such as ANFIS has been getting extremely popular in several applications [6].

To predict inflation, the Central Banks use a large information set coming from expert judgments, which is derived using both now casting tools, and a variety of models ranging from simple traditional time series models to theoretically well-structured dynamic stochastic general equilibrium (DSGE) models. [7]. Artificial neural networks and fuzzy neural networks are suitable tools for estimating and predicting many time series including inflation [6].

In this study, inflation rates in Turkey were predicted by ANFIS and ARIMA. The raw data are related to the country of the Turkey in the period of January 2005 and October 2021. As independent variables M1 money supply, $/₺ exchange rate and the interest rate of the Central Bank of Republic of Turkey were used. Min-max normalization was applied to the time series. The ANFIS model was found to be more successful than the ARIMA model.

LITERATURE REVIEW

There are a lot of study in the literature about the time series estimation using machine learning methods and conventional statistical methods. In this section, the studies carried out were given.

Hafer and Hein (1985) contrasted there different method to estimate the inflation. These models were a time series approach to modeling and forecasting inflation, an interest rate model developed and extended in Fama and Gibbsons (1984) and the responses to the American Statistical Association and National Bureau of Economic Research. As a result survey method provide the most accurate results [8, 27].

Sharda and Patil (1990), had a detailed literature review study and they reached the result of neural networks at least as successful as traditional statistical models [9, 28].

Hafer and Hein (1990) suggested that inflation forecasts derived from short-term interest rates are as accurate as time series forecasts. Using monthly Euro rates and the consumer price index (CPI) for the period 1967-86, their results indicated that time-series forecasts of inflation had equal or lower forecast errors and had unbiased prediction more often than the interest rate based forecasts [10, 29].

Caire et al. (1992), compared the neural networks (NN) and ARIMA results of the daily electric consumptions, and obtained the better results on NN [11].

Refenes (1993), in her study with hourly exchange rate time series data, concluded that ANN gives better predictive values than exponential smoothing and ARIMA models [11].

Bidarkota and Mcculloch (1998) argued that monthly inflation in the United States indicated abnormal in the form of either occasional big shocks or marked changes in the level of the series. They developed a univariate state space model with symmetric stable shocks for that series. The non-Gaussian model was estimated by the Sorenson Alspach filtering algorithm. Even after removing conditional heteroscedasticity, normality was rejected in favor of a stable distribution with exponent 1.83. Their model could be used for forecasting future inflation, and to simulate historical inflation forecasts conditional on the history of inflation. Relative to the Gaussian model, the stable model accounted for outliers and level shifts better, provided tighter estimates of trend inflation, and gave more realistic assessment of uncertainty during confusing episodes [10].

Moshiri and Cameron (2000), in their study comparing a feedback ANN with ARIMA, vector auto regression (VAR) and Bayesian VAR models, showed that ANN exhibits as good predictive performance as other classical models in predicting inflation and in some cases has better prediction performance than classical models [11, 30].

Kamruzzaman and Sarker (2003) conducted a study in which the Austrian Dollar was estimated using artificial neural network models created with six different cross rates and ARIMA. As a result of this study, they determined that the estimations made with ANN gave better results than the estimations made with ARIMA [11, 31].

Hahn (2003) investigated the pass-through of external shocks, i.e. oil price shocks, exchange rate shocks, and non-oil import price shocks to euro area inflation at different stages of distributions (import prices, producer prices and consumer prices). The analysis was based on VAR model that includes the distribution chain of pricing. According to results the pass-through was largest and forecast for non-oil import price shocks, followed by exchange rate chocks and oil price shocks. The size and the speed of the pass through of theses shocks declined along the distribution chain [10].

Ratfai (2004) studied by placing store-level price data into bivariate Structural VAR models of inflation and relative price asymmetry, this study evaluated the quantitative importance of idiosyncratic pricing shocks in short run aggregate price change dynamic [10].

Domaç (2004), in his study aiming to predict and define inflation for Turkey, stated that the best model among Profit Margin (Mark-Up) Models, Money Gap Models, Phillips Curve Model and ARIMA Model is Phillips Curve Model [11].

İnsel and Süalp (2008), using monthly data of the annual change in the nominal dollar exchange rate index, annual inflation rate, nominal interest rate on twelve-month deposits and the logarithm of real GNP in the Turkish economy between 1987 and 2007, Autoregressive Moving Average (ARMA) and compared the predictive performance of ANN models. As a result of the predictions made in the study, it is understood that the ANN model for inflation rate, exchange rate and interest rate, and the ARMA model for real GNP give better predictive values [11, 32].

Meçik and Karabacak (2011) showed the success of ARIMA models in inflation forecasting in their study on inflation forecasting in Turkey [12].

A notable example is Biau and D'Elia (2011), who applied the method to select variables that feed into a GDP forecasting model for the Euro area from a dataset containing 172 indicators; they found that it compares favorably with autoregressive forecasts and with those of the Eurozone Economic Outlook. Thus, their approach is very similar to the goal of our study, albeit with only one ML method being used, as an intermediate step and not to produce the forecast compared with the autoregressive benchmark [7].

Wohlrabe and Buchen (2014) , who evaluated its performance in forecasting economic variables for the Euro zone and the USA; Lehmann and Wohlrabe (2016), who used German data to assess the type of indicators usually selected by the method. Among the first examples of the application of neural networks for this type of problems are as follow: Swanson and White (1995, 1997), in finance; Stock and Watson (1998), who found that neural networks perform poorly in comparison to other univariate methods; Refenes and White (1998) and Fernández-Rodríguez et al. (2000), also in finance; and Moshiri and Cameron (2000), who forecast inflation [13].

Mombeini and Yazdani-Chamzini (2015) found the artificial neural network model more successful in their study in which they compared the multilayer artificial neural networks and the ARIMA model.

Kocatepe and Yıldız (2016) predicted the direction of change in gold prices with artificial neural networks and achieved a 75.24% success rate [14].

Varol (2016), made an inflation forecast with ANFIS according to the Central Bank of the Republic of Turkey data and showed that this method was successful in inflation forecasting [15].

Dubey (2016) compared the support vector regression ANFIS-GP and ANFIS-SC methods in gold price estimation and stated that the ANFIS-GP method is a more successful method. More recently, Nikolopoulos et al. (2016) used KNN to forecast sporadic demand in a supply chain setting. However, these studies did not attempt a systematic evaluation of the properties of the forecasts. The random forests (RF) algorithm was proposed by Breiman (2001) [13].

Bayramoğlu and Özturk (2017) estimated the inflation rate in Turkey using ARIMA and Gray System Models, and found the ARIMA model to be more successful in estimating Consumer Price Index (CPI) and the Gray System Model in estimating Producer Price Index (PPI) [16].

İlyas and Urfalıoğlu (2018) in their study based on exchange rates and interest rates between 2002 and 2015, they made an inflation forecast with ANFIS and Regression Analysis. According to the results, ANFIS has more realistic inflation forecasts than Regression Analysis [17].

Regardless of economic and financial forecasts Udod, Voronina and Ivchenkova (2020) developed and applied a softwareproduct to predict dental caries on the basis of neural network programming. The results showed that neural network and the software product based on it permit to predict the development of dental caries in persons of all ages with a probability of 83.56% [18, 33].

Bağcı (2021) compared the Gray models with the ARIMA model in her study for inflation forecasting in Turkey, and suggested that the ARIMA model was more successful [19].

All of these studies illustrate that neural networks and fuzzy logic are useful to predict the time series forecasting in finance and economic as that successful other areas.

METHODOLOGY

In this study, ARIMA and ANFIS methods were used for the inflation forecasting. These two models were explained below as subsections.

Autoregressive Integrated Moving Average (ARIMA)

Time series is a general name for data whose observations are ordered by time. In time series data, unlike other data, the order has an importance. More theoretically, the time series is a probabilistic process. On the other hand, time series data, is the realization of the probabilistic process. In time series encountered in real life, the time unit may be different. For example, while time series such as the values of mutual funds or the prices of cryptocurrencies followed in recent years are observed daily, time series such as gross domestic product (GDP) are observed quarterly. Time series can be named as daily, weekly, monthly, quarterly or annual depending on the frequency of their observation. Some time series are not named because they are not regular. Continuous time series are called continuous time series [20].

Among the traditional methods, ARIMA models are one of the recently developed predictive methods. ARIMA, which also found the inclusiveness of other models, benefited from entering the deficiencies in other models. Newbold and Granger have studied 50 series and revealed that the Box-Jenkins method gives more accurate and reliable results than other methods [21].

In the Box-Jenkins method, future values are estimated from the previous values in the series. However, this estimate takes into account the effect of linear combinations of error terms in the series. This method is effective in making Box-Jenkins more successful than other models. Box-Jenkins is also known as the Autoregressive Integrated Moving Average Method (ARIMA) in the literature. Box-Jenkins or ARIMA models can be expressed as a combination of AR and MA models applied to series with d-degree difference.

ARIMA linear models are used in many areas of time series estimation and stand out with their accuracy. The linear function is based upon three parametric linear components: autoregression (AR), integration (I), and moving average (MA) method. The autoregressive or ARIMA(p,0,0) method is represented as follows:

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + e_t \quad (1)$$

where p is the number of the autoregressive terms, Y_t is the estimated output, Y_{t-p} is the observation at time t-p, and f_1, f_2, ., f_p is a finite set of parameters. The f terms are determined by linear regression. The q_0 term is the intercept and et is the error associated with the regression. This time series depends only on p past values of itself and a random term e_t. The moving average or ARIMA(0,0,q) method is represented as

$$Y_t = \mu - \emptyset_1 e_{t-1} - \emptyset_2 e_{t-2} - \cdots - \emptyset_q e_{t-q} + e_t \quad (2)$$

where q is the number of the moving average terms, Q_1, Q_2, ., Q_q are the finite weights or parameters set, and m is the mean of the series. This time series depends only on q past random terms and a present random term et. As a particular case, an ARIMA (p,0,q) or ARMA (p,q) is a model for a time series that depends on p past values of itself and on q past random terms et. This method has the form of Eq.

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + e_t + \mu - \emptyset_1 e_{t-1} - \emptyset_2 e_{t-2} - \cdots - \emptyset_q e_{t-q} + e_t \quad (3)$$

Finally, an ARIMA(p,d,q) is a ARIMA(p,0,q) model for a time series that has been differenced d times [22].

Adaptive Neuro Fuzzy Inference System (ANFIS)

Almost all of the events that people encounter in daily life have a complex structure. This complex structure creates uncertainty. The situations that face this uncertainty are good, bad; hot, cold; It is due to the fact that it cannot be expressed with precise concepts such as far and near. The concept of fuzzy logic is a system of logic that overlaps with people's ability to think in imprecise terms. The logic of the find is the use of flexible expressions such as far, far, near, closer instead of precise concepts [23].

Fuzzy sets form the basis of fuzzy logic. A fuzzy set consists of elements expressed with the membership function μx; if these elements belong to the cluster fully, they have a membership degree of "1", if they do not belong at all; They are the elements that have a membership degree of "0" or that can take membership values between 0 and 1 in case of partial belonging.

Let A = {x|x = 2y + 1,y natural number} be a set encountered in classical mathematics. It is clear that A is the set of all odd natural numbers. Thus, any natural number x will be an element of A if it is odd. Otherwise, it is not an element of A. This situation is shown below in an ordered pair, the first element showing the degree of membership and the second element showing the number.

A={(1,1),(0,2),(1,3),(0,4),…} (4)

As can be seen, an element in a classical set either belongs to that set or does not belong to it. However, in fuzzy sets, there is a degree of belonging. This degree is expressed as the "membership degree" and is continuous in the range of [0, 1] [24].

Artificial Neural Networks (ANN) technique has emerged as a powerful modeling tool, which can be applied for many scientific and engineering applications, such as pattern reorganization, classification, data processing, and process control. ANN technique has some unique futures which distinguish them from other data processing systems include ability to work successfully even when they are party damaged, parallel processing, ability to make generalization, and little susceptibility to errors in data sets [17]. In addition, they known with the success in the time series estimations.

The Adaptive Neural Fuzzy Inference System (ANFIS) was developed by S. Roger Jang in 1992. It was developed by Takagi – Sugeno fuzzy model; given input and it is a neural fuzzy inference system that trains the output. ANFIS given entries while ensuring the best fit with the outputs, the feedback learning algorithm and the most A hybrid learning algorithm in which the little squares method is used together is applied [17].

In figure 1, the structure of the adaptive neuro fuzzy logic system with two input and 1-output variables is shown. For a two-input structure, the rules of the 1st degree ANFIS system can be written as follows.

Rule 1: IF x is A_1 and y is B_1 THEN
$f\_1=p_1{*}x+q_1{*}y+r_1$ (5)
Rule 2: IF x is A_2 and y is B_2 THEN
$f_2=p_2{*}x+q_2{*}y+r_2$ (6)

where, x and y; non fuzzy input values, p_1, q_1, r_1, p_2, q_2 and r_2 are the parameters of the output function of the inference system. ANFIS generally consists of the following steps below.

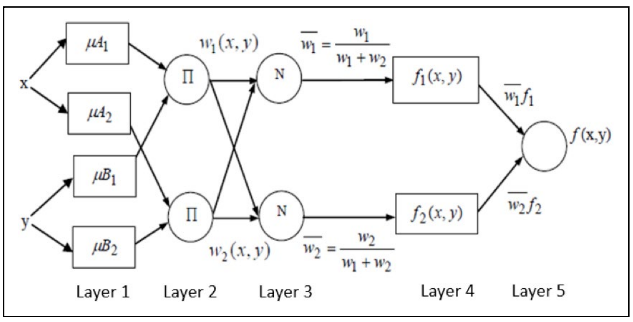


Figure 1. Structure of the Adaptive Neuro Fuzzy Logic System.

Input node (Layer 1): Each node in this layer represents the membership functions of the input variables and each output node is O_i^1 calculated as in equation (7).

$$O_i^1 = \mu_A(x) \qquad i = 1,2$$
$$O_i^1 = \mu_{Bi-2}(y) \quad i = 3,4 \tag{7}$$

Where, μ_{Ai} and μ_{Bi} ; Ai and Bi illustrate the membership functions of fuzzy sets. In this study, Gauss type membership function was used given in equation (8).

$$O_i^1 = \mu_{Ai}(x) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{8}$$

Rule node (Layer 2): Using the AND/OR operators for each node of in this layer, the input signals denoted by Π are multiplied and the firing force O_i^2 is obtained.

$$O_i^2 = w_i = \mu_{Ai}(x)\mu_{Bi}(y), \quad i = 1,2 \tag{9}$$

Mean node (Layer 3): In this layer, the firing forces obtained from each node are summed and normalized with the help of equation (10).

$$O_i^3 = \underline{w_i} = \frac{w_i}{w_1+w_2}, \quad i = 1,2 \tag{10}$$

Layer 4: In this layer, the contribution of each node to the model output is calculated.

$$O_i^4 = \underline{w_i}.f_i = \underline{w_i}(p_i x + q_i y + r_i) \tag{11}$$

Output node (Layer 5): In this layer, the overall output of the system is calculated and converted from fuzzy value to exact value by defuzzification [25].

$$f(x,y) = \frac{w_1(x,y)f_1(x,y) + w_2(x,y)f_2(x,y)}{w_1(x,y) + w_2(x,y)}$$
$$= \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{12}$$
$$O_i^5 = f(x,y) = \sum_i \overline{w_i}\, f_i = \overline{w_1} f_1 + \overline{w_2} f_2 = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{13}$$

APPLICATION

In this study, inflation rates in Turkey were estimated retrospectively using ARIMA and ANFIS models and the prediction success of the models were compared. In the ANFIS model, the Central Bank of the Republic of Turkey Policy Interest Rate, the Dollar-Turkish Lira index and the M1 money supply were used as independent variables. Data of the Central Bank of the Republic of Turkey were used. The data were taken monthly and the data of 202 months between 2005 January 2021 and October were used monthly [26].

The other method of the study is the ARIMA model. For the creation of the ARIMA model, the time series must be stationary. Auto correlation function (ACF) and partial auto correlation function (PACF) charts are a useful method for determining whether a time series is stationary.

The basic statistical values of the series are given at Table 1 below.

When the ACF graph analyzed in the Figure 2, it can be said that the series is not stationary since the AC value starts from a high value and decreases parabolic.

One of the methods used to understand whether the series is stationary is unit root tests. In this study, commonly used Augmented Dickey Fuller tests were performed. When we look at the Augmented Dickey Fuller unit root test results at Table 2 below, since the t-statistic value is not less than all of the test critical values, it is definitely not stationary at the serial level.

Since the series is not stationary, we need to take the difference of the 1st degree. The graph of the series whose first difference is taken is as Figure 3 below.

Augmented Dickey Fuller unit root tests also applied for the new obtained series. Moreover results are given in the Table 3 below.

Since the t statistic is less than all critical values in the series, it can be accepted that the series has reached stationarity. ACF function graph, which is another method that

Table 1. Statistical Values of the Time Series

Statistical Metrics	Value
Observations	202
Mean	10.02525
Median	9.1
Maximum Value	25.24
Minimum Value	3.99
Standard Deviation	3.803755
Skewness	1.5752
Sum	2025.1
Sum Sq. Dev.	2908.179

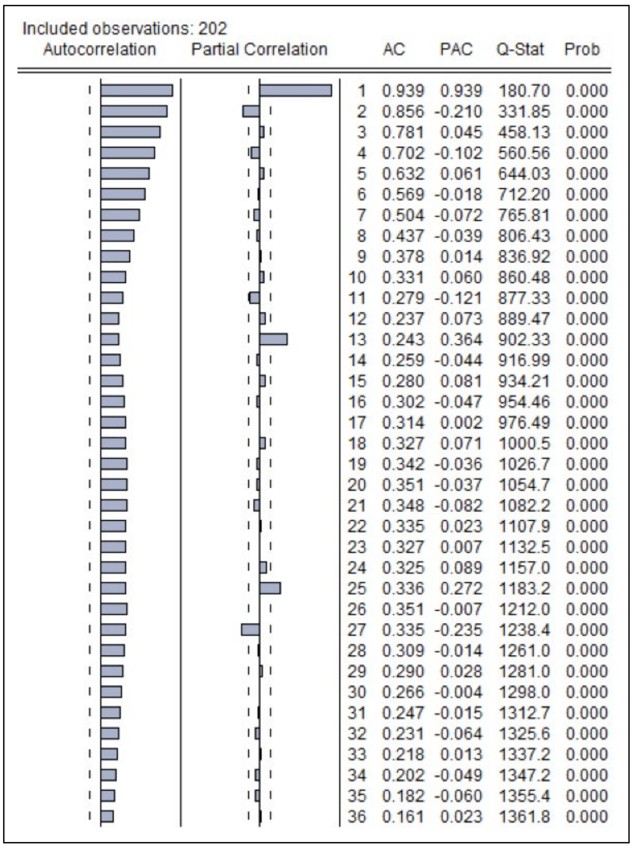


Figure 2. ACF and PACF Graphs of the Time Series.

Table 2. Constant Term ADF, Constant and Trend Term ADF and Constant Termless ADF Unit Root Tests

Augmented Dickey-Fuller Unit Root Test Type	Constant Term		Constant and Trend Term		Constant Termless	
	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
Augmented Dickey-Fuller Test Statistic	-0.656359	0.8536	-3.106518	0.1076	0.674133	0.8606
Test Critical Values						
1% level	-3.465014		-4.004599		-2.577255	
5% level	-2.876677		-3.432452		-1.942517	
10% level	-2.574917		-3.139991		-1.615583	

Table 3. Constant Term ADF, Constant and Trend Term ADF and Constant Termless ADF Unit Root Tests

Augmented Dickey-Fuller Unit Root Test Type	Constant Term		Constant and Trend Term		Constant Termless	
	t-Statistic	Prob.*	t-Statistic	Prob.*	t-Statistic	Prob.*
Augmented Dickey-Fuller Test Statistic	-7.223638	0	-6.291222	0	-7.171876	0
Test Critical Values						
1% level	-3.465014		-4.007882		-2.577255	
5% level	-2.876677		-3.434036		-1.942517	
10% level	-2.574917		-3.140923		-1.615583	

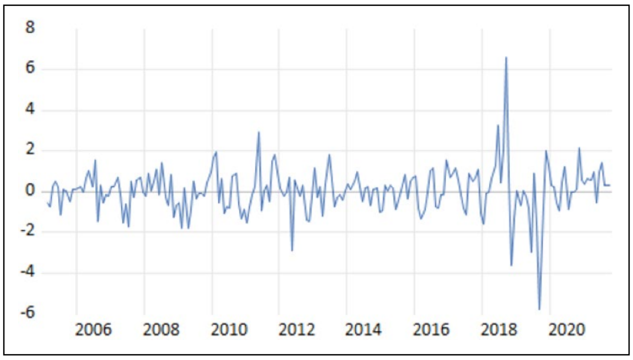


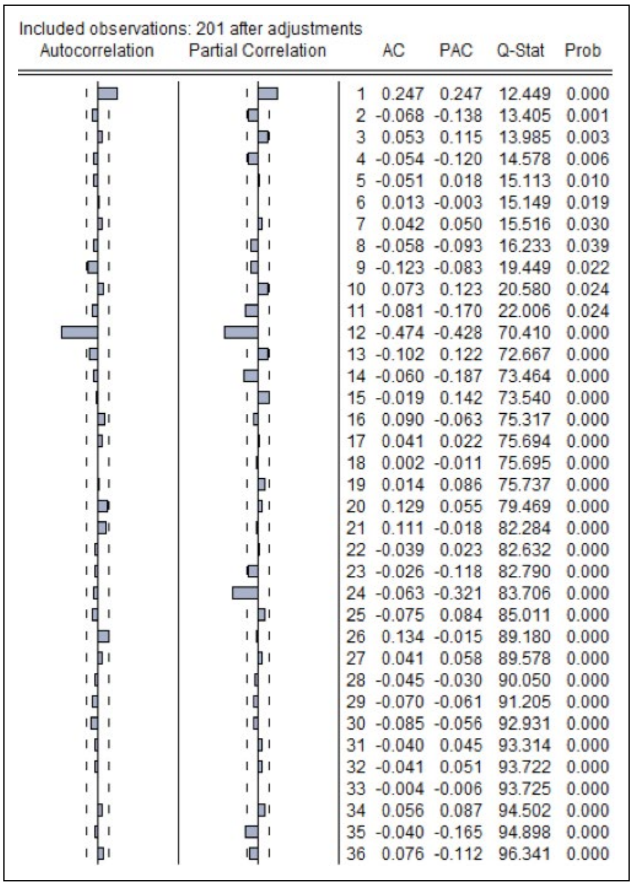
Figure 3. Line chart of the time series taken 1st degree difference.

can be used about stationarity, is given as Figure 4 below. As can be seen, there is no gradual decrease in AC value starting from a large value. AC value suddenly decreased. From here, it can be understood once again that the series has reached stationarity.

As understood from the Akaike Information Criteria graph below, the best ARIMA model of the 1st degree differenced time series is ARMA(4,12). In ARIMA(p,d,q) notation, "d" denotes how many times the difference is taken. Since the difference is taken once in this model, the optimum model is accepted as ARIMA(4,1,12).

Statistical values of the accepted model ARIMA(4,1,12) illustrates below as Figure 6.

When the unit root test was applied to the error values of the estimation values, it was observed that the error



Included observations: 201 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.247	0.247	12.449	0.000
		2	-0.068	-0.138	13.405	0.001
		3	0.053	0.115	13.985	0.003
		4	-0.054	-0.120	14.578	0.006
		5	-0.051	0.018	15.113	0.010
		6	0.013	-0.003	15.149	0.019
		7	0.042	0.050	15.516	0.030
		8	-0.058	-0.093	16.233	0.039
		9	-0.123	-0.083	19.449	0.022
		10	0.073	0.123	20.580	0.024
		11	-0.081	-0.170	22.006	0.024
		12	-0.474	-0.428	70.410	0.000
		13	-0.102	0.122	72.667	0.000
		14	-0.060	-0.187	73.464	0.000
		15	-0.019	0.142	73.540	0.000
		16	0.090	-0.063	75.317	0.000
		17	0.041	0.022	75.694	0.000
		18	0.002	-0.011	75.695	0.000
		19	0.014	0.086	75.737	0.000
		20	0.129	0.055	79.469	0.000
		21	0.111	-0.018	82.284	0.000
		22	-0.039	0.023	82.632	0.000
		23	-0.026	-0.118	82.790	0.000
		24	-0.063	-0.321	83.706	0.000
		25	-0.075	0.084	85.011	0.000
		26	0.134	-0.015	89.180	0.000
		27	0.041	0.058	89.578	0.000
		28	-0.045	-0.030	90.050	0.000
		29	-0.070	-0.061	91.205	0.000
		30	-0.085	-0.056	92.931	0.000
		31	-0.040	0.045	93.314	0.000
		32	-0.041	0.051	93.722	0.000
		33	-0.004	-0.006	93.725	0.000
		34	0.056	0.087	94.502	0.000
		35	-0.040	-0.165	94.898	0.000
		36	0.076	-0.112	96.341	0.000

Figure 4. ACF and PACF Graphs of the Time Series.

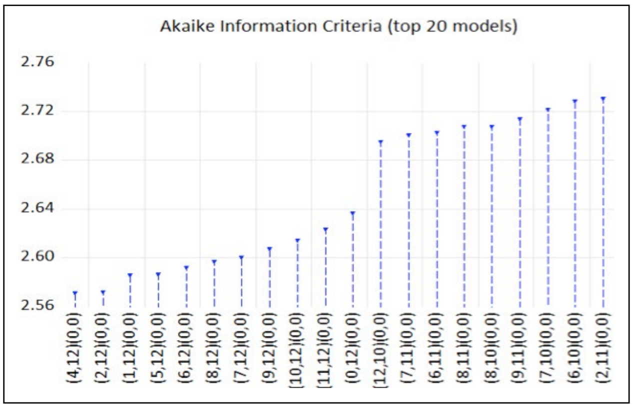


Figure 5. Akaike Information Criteria of Top 20 Models.

Dependent Variable: D1Inflation
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/16/22 Time: 14:47
Sample: 2005M02 2021M10
Included observations: 201
Convergence achieved after 30 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.038440	0.016051	2.394832	0.0176
AR(4)	-0.060439	0.104765	-0.576896	0.5647
MA(12)	-0.854972	0.067530	-12.66068	0.0000
SIGMASQ	0.702018	0.035785	19.61749	0.0000

R-squared	0.451623	Mean dependent var	0.052985
Adjusted R-squared	0.443272	S.D. dependent var	1.134273
S.E. of regression	0.846329	Akaike info criterion	2.602116
Sum squared resid	141.1057	Schwarz criterion	2.667854
Log likelihood	-257.5127	Hannan-Quinn criter.	2.628716
F-statistic	54.08061	Durbin-Watson stat	1.426533
Prob(F-statistic)	0.000000		

Inverted AR Roots	.35-.35i	.35-.35i	-.35+.35i	-.35+.35i
Inverted MA Roots	.99	.85+.49i	.85-.49i	.49+.85i
	.49-.85i	-.00-.99i	-.00+.99i	-.49-.85i
	-.49+.85i	-.85+.49i	-.85-.49i	-.99

Figure 6. Statistical Values of ARIMA (4,1,12).

values were stationary and statistically significant. In the Figure 7, Table 4 and Appendix 2 line graph of the error values, statistical values and ACF - PACF graphs of the error values can be seen. When these data investigated, it is shown that Augmented Dickey-Fuller test statistic of the error series is lower than all test critical values and it means error time series is statistically significant. Moreover time series is stationary from the ACF and PACF graphs. The errors of the ARIMA and ANFIS models are presented in Table 5.

eViews software was used in the estimation study with

Table 4. Statistical Values of the Error Values Time Series

	t-Statistic	Prob.*
Augmented Dickey-Fuller Test Statistic	-9.999151	0
Test Critical Values		
1% level	-4.004836	
5% level	-3.432566	
10% level	-3.140059	

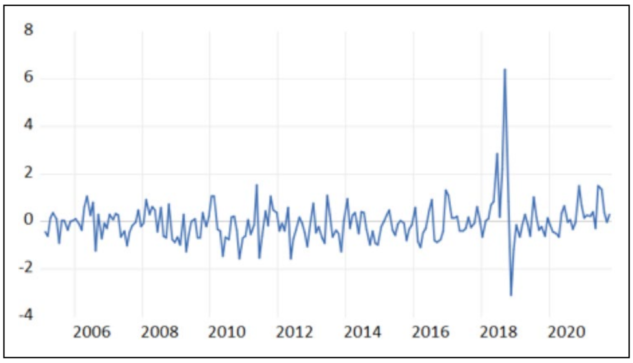


Figure 7. Line Graph of the Error Values.

Table 5. Error Criteria Comparison of ARIMA and ANFIS Models

Method	RMSE	R^2	MAE	SMAPE
ANFIS	0.028	0.97	0.64	0.07
ARIMA	0.85	0.95	0.58	1.14

ARIMA. Static estimation values have been taken as a basis, since retrospective estimations are made from existing values. The results of the estimation with ARIMA(4,1,12) are shown in Figure 8 as a line graph.

In Figure 9 below, the actual values and the estimation results made by ARIMA(4,1,12) are shown on the same graph in comparison.

In the ANFIS model, min-max normalization was applied to the data. The mathematical equation for the min-max normalization is given below.

$$X_{new} = \frac{X_i - min\,(x)}{(x) - min\,(x)} \tag{14}$$

In the ANFIS model 202 monthly values divided into %30 testing and %70 training data randomly. It means 141 value separated for the training whereas 61 value for test. MATLAB software was used for the modelling. The model was run with different membership functions, different membership function numbers and different membership function types, and the study was continued with the com-

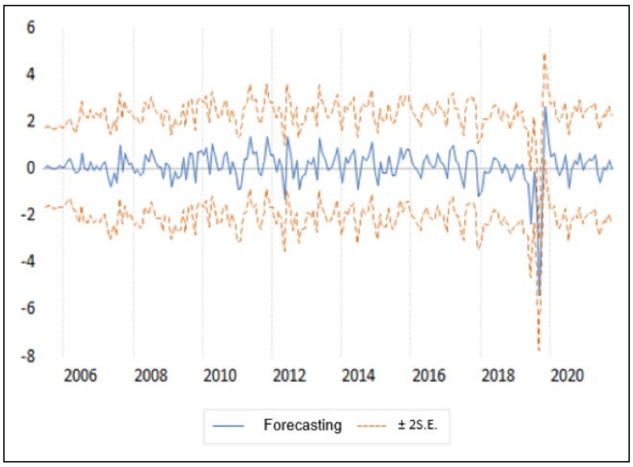


Figure 8. Estimation Results.

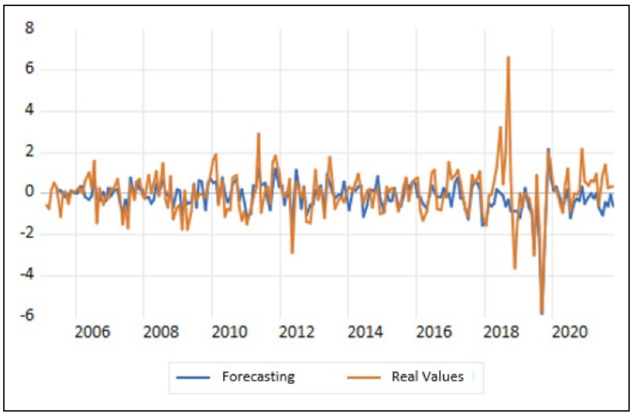


Figure 9. Comparison of Real Values and the Estimation Values.

bination with the lowest error. In the Appendix 1 results of the combinations were given. According to the error value the most feasible combination is evaluation of product of two sigmoidal membership functions (psigmf) with linear type and 4 4 4 layer. In this case, 0.02816 error has been reached with training data. Than the same processes applied for the test data and found the 0.071477.

The coefficients of certainty and graphs between the estimation results of the test and the training data and the real values exported are shown in Figure 10 below.

Inverse normalization was applied to the estimation results. As a result, actual inflation values and forecast results are shown in Figure 11 on the same graph.

The estimation results made with ANFIS and ARI-

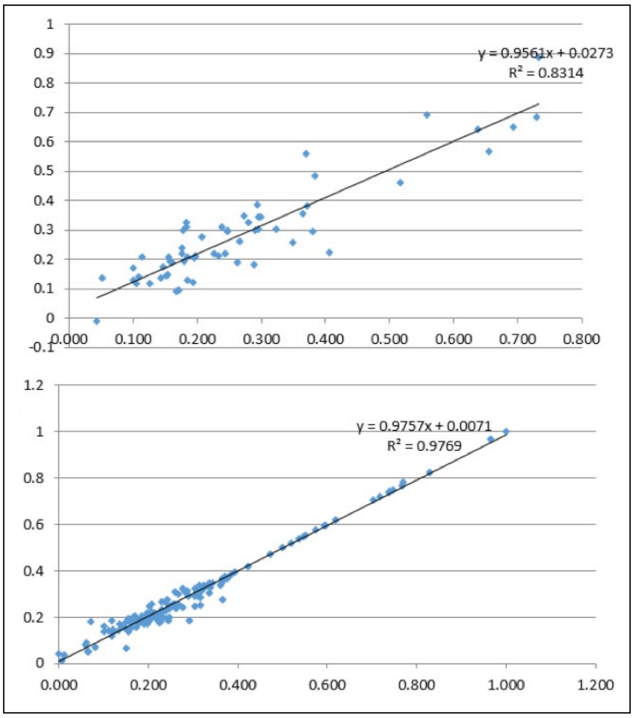


Figure 10. R^2 of the Training Data. R^2 of the Test Data.

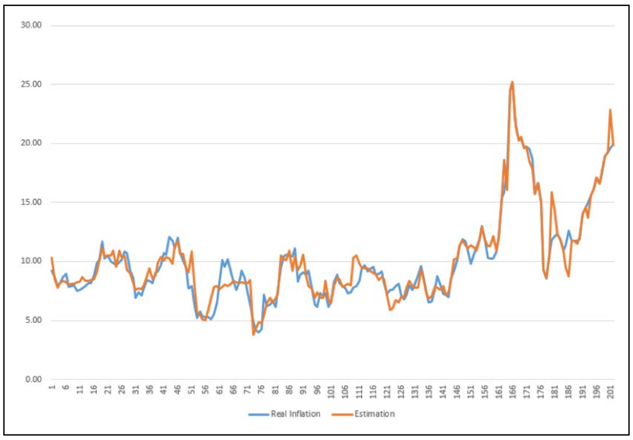


Figure 11. Prediction and true value comparison after inverse normalization.

MA were compared according to root mean square error (RMSE), coefficient of determination (R^2), mean absolute error (MAE) and symmetric mean absolute percentage error (SMAPE) performance criteria. ANFIS model have 0.028 RMSE value whereas ARIMA has 0.85. When the R^2 values are compared, ANFIS model has higher value than ARIMA with 0.97. Compared to the MAE, the ARIMA model is slightly more successful with a value of 0.58 than the ANFIS model with a value of 0.64. ANFIS model has 0.07 SMAPE value when ARIMA has 1.14.

CONCLUSIONS

In this study, retrospective inflation estimation was made with ARIMA, which is a traditional forecasting method, and ANFIS, which is a heuristic method. The data series used cover the months of January 2005 and October 2021. While estimating from previous inflation values in ARIMA, Central Bank Policy Interest Rate, Turkish Lira American Dollar Rate and M1 money supply were used as independent variables in ANFIS. Estimation results were compared according to different performance criteria. When the error criteria table above is examined, it is seen that the error in the estimation results made with the ANFIS model is lower than the error in the estimation results made with the ARIMA model. As a result of the study, it was concluded that both models were successful in long-term inflation predictions, but ANFIS was more successful than ARIMA. This study can be improved by using different time series methods and different heuristics in future studies. Instead of the independent variables using in this study, different variables such as unemployment rate or commodity prices may be used. With similar methods, inflation rates in different countries may be predicted and compared with the results of this study.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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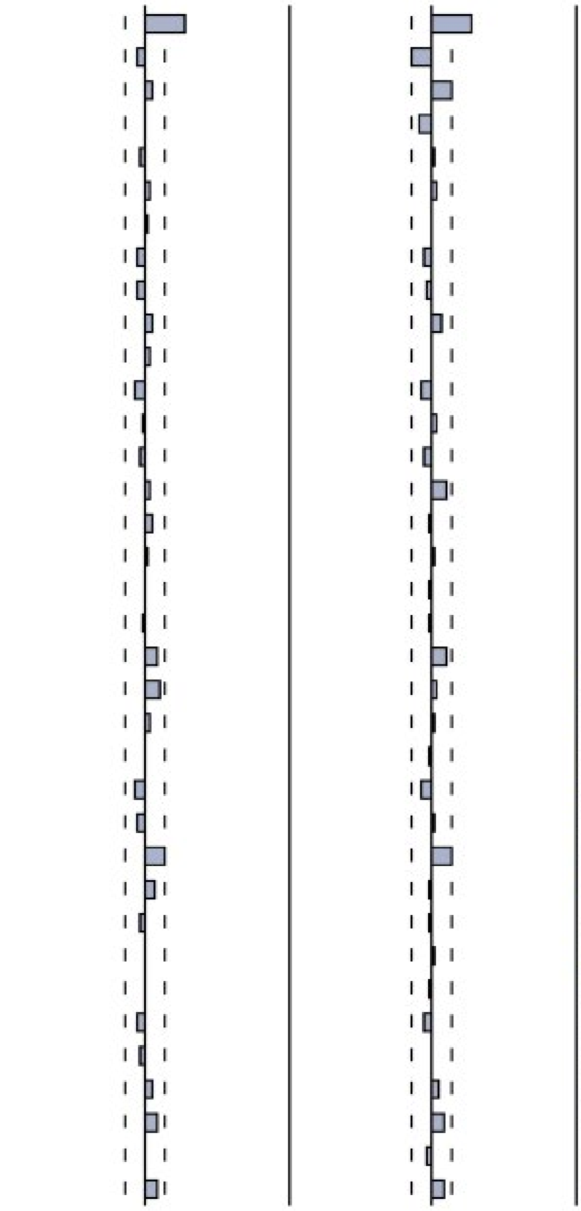
Appendix 1. Model Combination Values

Training				
Membership Function	**Membership Function Type**	**Membership Function Layers**	**Epochs**	**Error**
trimf	constant	4 4 4	100	0.039700
trimf	Linear	4 4 4	100	0.029953
trimf	constant	3 3 3	100	0.051570
trimf	Linear	3 3 3	100	0.032791
trapmf	constant	4 4 4	100	0.041100
trapmf	Linear	4 4 4	100	0.028755
trapmf	constant	3 3 3	100	0.054963
trapmf	Linear	3 3 3	100	0.033732
gbellmf	constant	4 4 4	100	0.037000
gbellmf	Linear	4 4 4	100	0.026970
gbellmf	constant	3 3 3	100	0.046851
gbellmf	Linear	3 3 3	100	0.032461
gaussmf	constant	4 4 4	100	0.035927
gaussmf	Linear	4 4 4	100	0.027476
gaussmf	constant	3 3 3	100	0.045967
gaussmf	Linear	3 3 3	100	0.032824
gauss2mf	constant	4 4 4	100	0.039600
gauss2mf	Linear	4 4 4	100	0.026986
gauss2mf	constant	3 3 3	100	0.052949
gauss2mf	Linear	3 3 3	100	0.032494
pimf	constant	4 4 4	100	0.042375
pimf	Linear	4 4 4	100	0.030217
pimf	constant	3 3 3	100	0.052063
pimf	Linear	3 3 3	100	0.032439
dsigmf	constant	4 4 4	100	0.03830
dsigmf	Linear	4 4 4	100	0.025823
dsigmf	constant	3 3 3	100	0.043005
dsigmf	Linear	3 3 3	100	0.032149
psigmf	constant	4 4 4	100	0.038300
psigmf	Linear	4 4 4	100	0.028160
psigmf	constant	3 3 3	100	0.043000
psigmf	Linear	3 3 3	100	0.032149

Sample (adjusted): 2005M02 2021M10
Included observations: 201 after adjustments

Autocorrelation Partial Correlation



	AC	PAC	Q-Stat	Prob
1	0.284	0.284	16.461	0.000
2	-0.061	-0.154	17.224	0.000
3	0.064	0.143	18.073	0.000
4	-0.004	-0.090	18.077	0.001
5	-0.036	0.018	18.349	0.003
6	0.034	0.027	18.592	0.005
7	0.020	-0.002	18.673	0.009
8	-0.059	-0.059	19.407	0.013
9	-0.062	-0.033	20.228	0.017
10	0.052	0.078	20.801	0.023
11	0.039	-0.006	21.122	0.032
12	-0.069	-0.068	22.159	0.036
13	-0.011	0.026	22.184	0.053
14	-0.031	-0.063	22.387	0.071
15	0.031	0.103	22.603	0.093
16	0.050	-0.019	23.161	0.110
17	0.012	0.013	23.191	0.143
18	-0.003	-0.009	23.192	0.183
19	-0.018	-0.010	23.261	0.226
20	0.085	0.113	24.893	0.206
21	0.111	0.031	27.696	0.149
22	0.031	0.014	27.921	0.178
23	-0.007	-0.021	27.934	0.218
24	-0.068	-0.071	28.993	0.220
25	-0.051	0.010	29.600	0.240
26	0.131	0.135	33.614	0.145
27	0.071	-0.015	34.808	0.144
28	-0.030	-0.014	35.015	0.169
29	-0.003	0.009	35.017	0.204
30	-0.007	-0.011	35.029	0.242
31	-0.056	-0.057	35.786	0.254
32	-0.029	-0.001	35.996	0.287
33	0.063	0.062	36.971	0.291
34	0.090	0.097	38.954	0.257
35	0.002	-0.026	38.955	0.296
36	0.088	0.087	40.883	0.265

Appendix 2. ACF and PACF graphs of the Error Values Time Series.