MODELLING THE INFLATIONARY PROCESSES AND FORECASTING: AN APPLICATION OF ARIMA, SARIMA MODELS

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Abstract

The purpose of this research is to model the inflationary processes on the based of autoregressive and moving average processes and determine the short-term inflation forecasting model. Modelling the inflationary processes and forecasting estimation assume great importance while developping the investment projects, indexation of wages, predetermining the macroeconomic policy and preventive measures. The advanced forecasting models such as ARIMA and SARIMA have been applied in this study.

Keywords: ARIMA, SARIMA, inflationary processes, forecasting.

JEL classification Codes: P24; P44; C53; E27

Introduction

Inflationary processes and forecasting the inflation originated from complex combination of these ones assume a great importance both in micro and macro economic level. Short-term inflation forecasting is the necessary component of monetary policy. There are several research approaches such as ARIMA, SARIMA, periodogram analysis and Fourier series, ARCH, GARCH, models to forecast the inflation volatility and rates. Of course, it is possible to happen the non-economic shock factors to change the macro economic stability including price stability. These shocks can not be predetermined in advance in the world. If the markets act on the competitive market principles without political and administrative interference in such case the made forecasting will fit the forecasted data in future. Because without interference there all processes is randomly developped in the framework of economic system.

1. Research works in the world

There several research work in this field. Ezekiel N.N.Nortey,Benedict Mbeah-Baiden, Julis B.Dasah and Feliks O.Mettle forecasted the inflation with ARCH modelling[1]. S.O.Adams, A.Awujola, A.İ.Alumgudu used the ARIMA models to forecast the inflation rate in Nigeria and got the adequate results [2]. Ekpenyong, Emmanuel John, Omekara C.O. forecasted the inflation using the periodoqram və Fourier series[3]. Sani Doguwa və Sara O.Alade used the SARIMA model to forecast the inflation in Nigeria[4].

2. Methodology and data

a. Theoretical framework and methodology

There are five different economic forecasting approaches based on times series data.

1. Exponential smoothing methods
2. Single equation regression models
3. Simultaneous equation regression models
4. **Autoregressive integrated moving average models(ARIMA)**
5. Vector autoregressiion

Forecasting on simultaneous equation regression models has subsided because of their poor forecasting performance, especially since the 1973 and 1979 oil price shocks because of OPEC oil embargoes and as well as because of Lucas critique [5,p. 837]. The essence of this critique is that the parameters obtained from an econometric model are dependent on the policy prevailing at the time the model was estimated. So, model will change if there is a policy change.

Briefly,the estimated parameters of the model are not stable in case of being the policy changes [6]. Box-Jenkins (BJ) methodology is known as ARIMA methodology. These models aren`t been set on the single equation models or simultaneous equation models. Such models are based on the stochastic features of times series.ARIMA is more suitable model. So, these kind of models enable to introduce the more reliable prediction [7].

VAR methodology resembles simultaneous-equation modeling wherein we consider several endogenous variables together. Whereas each endogenous variable is explained by its lagged, or past, values and the lagged values of all other endogenous variables in the model. So, as usual there are no exogenous variables in the model [5,p. 837].

In generally we can write the autoregression processes as follows:

$$(P_t - \delta) = \alpha_1(P_{t-1} - \delta) + \alpha_2(P_{t-2} - \delta) + \cdots + \alpha_p\left(P_{t-p} - \delta\right) + u_t \quad (1)$$

Here, $\delta - is\ a\ mean\ of\ P$. But, $u_t -$zero mean and constant variance σ^2 uncorrelated random error term(white noise). $u_t \sim IN(0, \sigma_u^2)$.

$P_t -$ is consumer price index at time t. This is also called p-th order autoregression processs and noted as $AR(p)$.

AR process is not the only process generated by P. In general form $MA(q)$ processes can be shown as follows.

$$P_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \cdots + \beta_q u_{t-q} \quad (2)$$

Here, $\mu -$ constant. $u -$ white noise stochastic error term. $u_t \sim IN(0, \sigma_u^2)$.

ARIMA models include p avtoregressive and q moving average terms. Therefore such models are called the ARIMA models. Stationarity problem may change depending on times series period. It is known that the most times series are non-stationary. It changes the integrated order of the series. ARIMA model in generally can be written as follows.

$$P_t = \theta + \alpha_1 P_{t-1} + \alpha_2 P_{t-2} + \cdots + \alpha_p P_{t-p} + \beta_0 \varepsilon_t - \beta_1 \varepsilon_{t-1} - \beta_2 \varepsilon_{t-2} - \cdots - \beta_q \varepsilon_{t-q} \quad (1)$$

ARIMA is non-seasonal times series model. The differencing linear operator in the model is noted as Δ .

$$\Delta P_t = P_{t-1} = P_t - BP_t = (1-B)P_t \quad (3)$$

The general form of the above mentioned ARIMA model with integrated order ARIMA (p, d, q) can be defined as below mentioned:

$$\alpha_p(B)(1-B)^d P_t = \mu + \beta_q(B)\varepsilon_t \quad (4)$$

$$\left(1 - \alpha_1 B - \alpha_2 B^2 - \ldots - \alpha_p B^p\right) P_t = (1 - \beta_1 B - \beta_2 B^2 - \cdots - \beta_q B^q)\varepsilon_t \quad (5)$$

$$\alpha(B) P_t = \beta(B)\varepsilon_t \quad (6)$$

ARIMA model is based on Box-Jenkins (BJ) methodology. This methodology consists of four stages: *Identification. Estimation. Diagnostic checking. Forecasting*. In most cases such models can generate the more reliable results. The figures R^2, Akaike info criteria(AIC), SIC, $RMSE, MAE, MAPE$ and TIC obtained from the models should be compared and the model having the least indicator should be considered the best model [8].

In this study seasonal adjusted ARIMA model (SARIMA) və non-seasonal ARIMA model have been applied and the results are compared on diagnostic basis. Seasonal ARIMA proseseses having the times series $\{P\_t\}\, t \in Z\ ARIMA(p, d, q)(P, D, Q)[S]$ aşağıdakı kimi ifadə olunur:

$$\alpha(L)\varphi(L^s)(1-L)^d(1-L^s)^D P_t = \beta(L)\Theta(L^s)\epsilon_t \qquad (7)$$

Here, L –standard backward operator, φ and Θ on the variable L^s with polynomials integrated orders P and Q seasonal avtoregressive (AR) and moving average (MA).

$AR(p) - p$ th order avtoregression term can be noted as follows:

$$\alpha(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_p L^p \qquad (8)$$

$MA(q) - q$ th order moving average term can be noted as follows:

$$\beta(L) = 1 + \beta_1 L - \beta_2 L^2 - \cdots - \beta_q L^q \qquad (9)$$

p th order seasonal avtoregression terms are as follows:

$$\varphi(L^s) = 1 - \varphi_1 L^s - \varphi_2 L^{2s} - \cdots - \varphi_p L^{Ps} \qquad (10)$$

q th order seasonal moving average terms are formulated as follows:

$$\Theta(L^s) = 1 + \Theta_1 L^s + \Theta_2 L^{2s} + \cdots + \Theta_p L^{Qs} \qquad (11)$$

s –number of periods in the season. $(1-L)^d - d$ order difference $I(d)$. This can be named as integrated order. $(1-L^s)^D - D$ order seasonal difference $I_s(D)$.

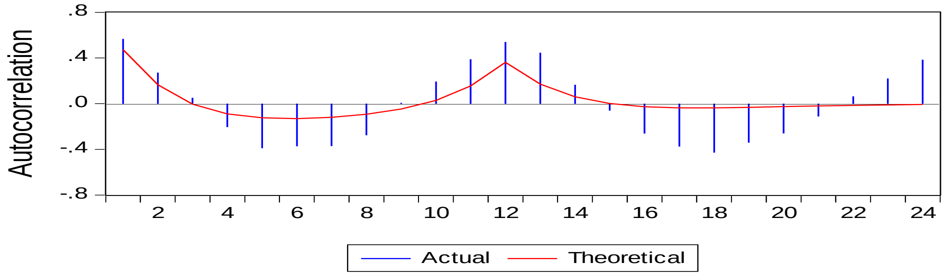
b. Data

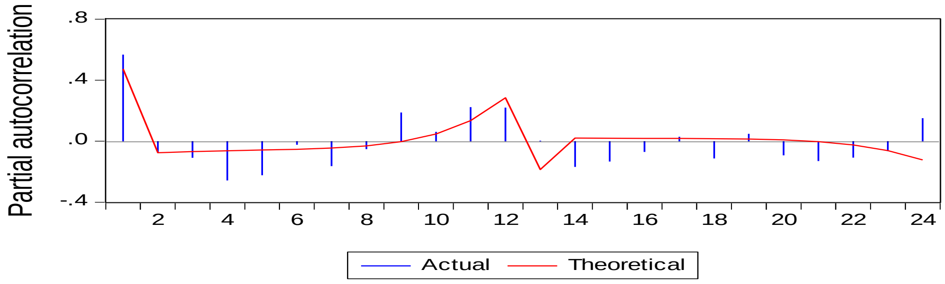
The data used in this study were obtained from the statistics bulletin of Central Bank of Azerbaijan[10].The data covers the period starting from 2009 until 2014 on monthly basis.

3. Implementation of SARIMA and ARIMA models and results of the models.

Models show that the diagnostic results of the model such as - LM test, ARCH test, normality test become statistical significant. Wheraas White test was statistical insignificant.

Graph.1. Residuals ACF and PACF functions





Q-statistics points that there is no auto correlation. As it seems from the correlogram the are some spikes in the 1st and 12th lags.(See.Annex1.Graph.2.)

Let`s look at the results obtained from the application of ARIMA. Constructed multiplicative SARIMA(1,0,1)(0,0,1)x12 model is as follows.

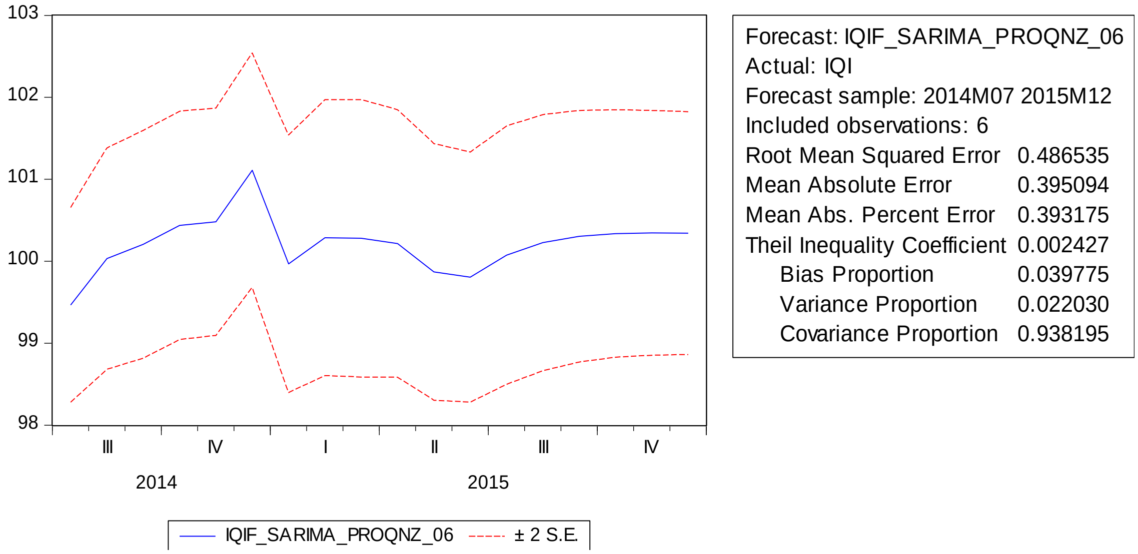
$$(1-\alpha_1 L-\alpha_2 L^2)P_t = (1+\beta_1 L)(1+\Theta_1 L^{12})\epsilon_t \quad (12)$$

Table.1. SARIMA(1,0,1)(0,0,1)x12			
Variable	Coefficients	t-Statistics	Prob.
C	100.2804	688.0120	0.0000
	[0.145754]		
AR(1)	1.347068	6.295969	0.0000
	[0.213957]		
AR(2)	-0.468569	-3.501751	0.0008
	[0.133810]		
MA(1)	-0.845638	-4.538298	0.0000
	[0.186334]		
SMA(12)	0.454063	3.358619	0.0013
	[0.135193]		

The estimated SARIMA(1,0,1)(0,0,1)x12 model are as follows.

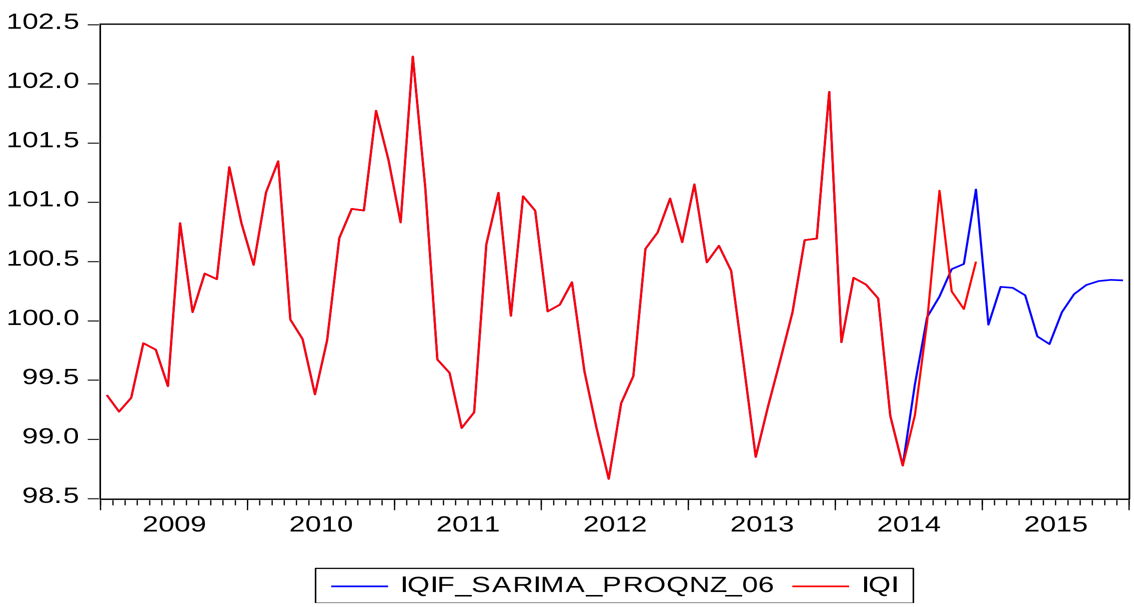
$$P_t = 100.28 + 1.34P_{t-1} - 0.46P_{t-2} - 0.84\epsilon_{t-1} + 0.45\epsilon_{t-12} - 0.38397\epsilon_{t-13}$$

Graph.3. SARIMA(1,0,1)(0,0,1)x12 model loss function



Bias proportion equals to 0.039775. In order to determine the best fit model we use $RMSE$-0.486535, MAE-0.395094, $MAPE$-0.393175 and TIC-0.002427.(see. Graph.3)

Graph.4. Inflation dynamics forecasted on the model SARIMA(1,0,1)(0,0,1)x12



Let`s look at an other SARIMA model- SARIMA(2,0,2)(1,0,0)x12:

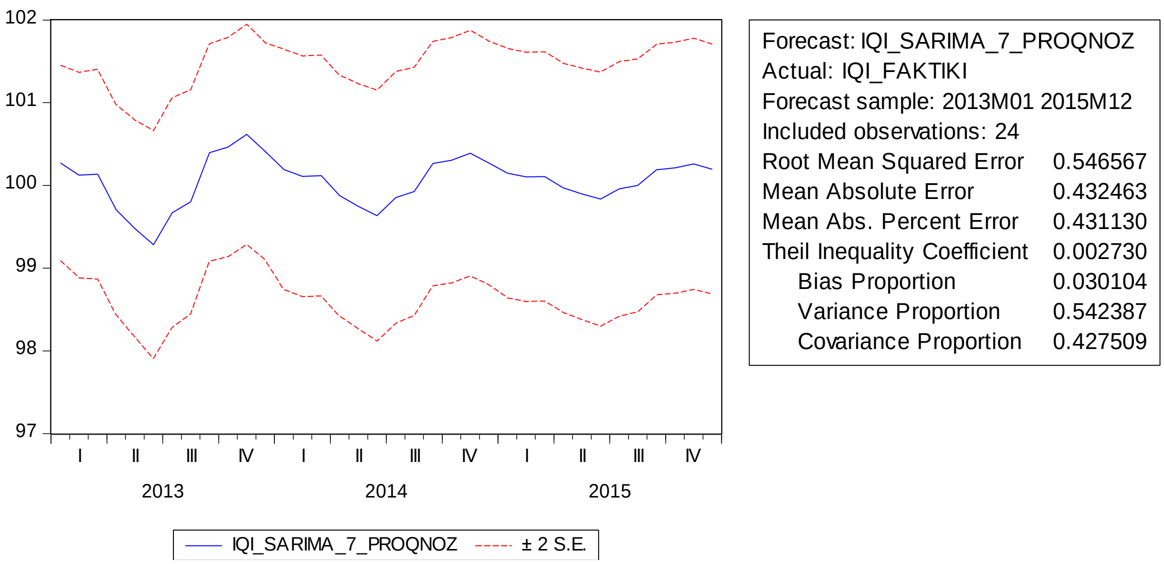
Table.2. Results of SARIMA(2,0,2)(1,0,0)x12.

Variable	Coefficients	Std. error	Prob.
C	100.0933	0.278618	0
AR(1)	1.012855	0.284939	0.0008
AR(2)	-0.51392	0.224334	0.0261
SAR(12)	0.566002	0.118397	0
MA(1)	-0.77715	0.300845	0.0126
MA(2)	0.54498	0.197902	0.0081

The estimated SARIMA(1,0,1)(0,0,1)x12 model are as follows.

$$P_t = 100.09 + 1.01P_{t-1} - 0.51P_{t-2} + 0.56P_{t-12} - 0.573P_{t-13} - 0.777\epsilon_{t-1} + 0.54\epsilon_{t-2}$$

Graph.6. SARIMA(2,0,2)(1,0,0)x12 model statistics loss functions



As above mentioned R^2, AIC, SIC, $RMSE$, MAE, $MAPE$ and TIC obtained from the models are compared in order to fix the fit model. So, due to the statistic loss function indicators SARIMA(2,0,2)(1,0,0)x12 model is considered to be worse than SARIMA(1,0,1)(0,0,1)x12.(see.Graph 6).

Table.3. Model description

ARIMA structure	Parametrs	Coefficients	Standardd error	P-value	R^2	Akaike criteria	Schwarz criteria
ARIMA(2,0,1)	C	100.2926	0.090057	0.0000	0.388184	1.949043	2.077528
	AR(1)	1.394135	0.181354	0.0000			
	AR(2)	-0.586309	0.110206	0.0000			
	MA(1)	-0.783051	0.194569	0.0001			
ARIMA(6,0,1)	C	100.2836	0.094647	0.0000	0.476243	1.930067	2.195480
	AR(1)	-0.364031	0.130477	0.0071			
	AR(2)	0.451225	0.116792	0.0003			
	AR(3)	0.017287	0.132519	0.8967			
	AR(4)	-0.060884	0.128596	0.6377			
	AR(5)	-0.323912	0.110715	0.0049			
	AR(6)	-0.222988	0.106125	0.0400			
	MA(1)	0.999949	0.048372	0.0000			
ARIMA(5,0,4)	C	100.2928	0.085467	0.0000	0.581795	1.763970	2.093029
	AR(1)	1.116979	0.128963	0.0000			
	AR(2)	-0.612542	0.116807	0.0000			
	AR(3)	0.856034	0.081601	0.0000			
	AR(4)	-1.160392	0.116454	0.0000			
	AR(5)	0.271697	0.129597	0.0405			
	MA(1)	-0.779660	0.032446	0.0000			
	MA(2)	0.295043	0.042696	0.0000			
	MA(3)	-0.767063	0.032021	0.0000			
	MA(4)	0.925151	0.024526	0.0000			

Let`s look at diagnostic test results of ARIMA model. There is heteroscedasticity problem in the model SARIMA (1,0,1)(0,0,1)x12. Stationarity requirement is provided by test.(Annex.1.Table.4.)

Table.5. ARIMA model diagnostic test results.

Testlər	**ARIMA(2,0,1)**		**ARIMA(6,0,1)**		**ARIMA(5,0,4)**	
	F-stat.	**P-val.**	**F-stat.**	**P-val.**	**F-stat.**	**P-val.**
Breusch-Godfrey Serial Correlation LM Test:						
	2.157050	0.1240	0.989137	0.3783	1.671701	0.1973
Heteroskedasticity Test: ARCH						

	0.005700	0.9400	0.613619	0.4364	0.002944	0.9569
Heteroskedasticity Test: White						
	0.795490	0.6697	0.747056	0.7972	2.527891	0.4684
Normality test	0,3129		0,1102		0,426	

So, let`s look at the diagnostic test results of SARIMA (1, 0, 1) (0, 0, 1) x12:

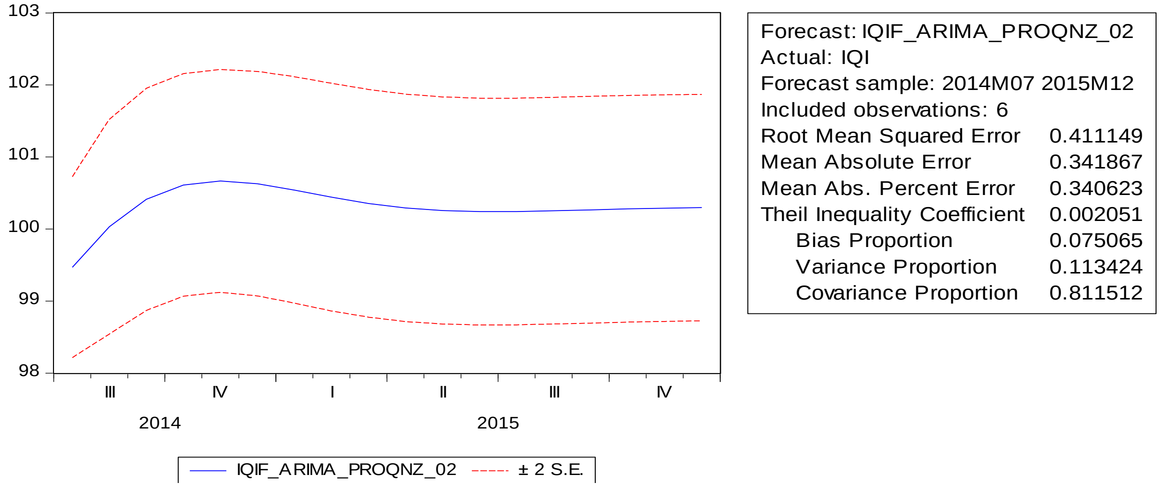
Table.6. SARIMA (1, 0, 1)(0,0,1)x12 model diagnostic test results.		
Testlər		
	F-statistika	**P-qiymət**
Breusch-Godfrey Serial Correlation LM Test:	0.870505	0.4237
Heteroskedasticity Test: ARCH	1.784194	0.1862
Heteroskedasticity Test: White	2.064974	0.0201
Normality test	0,578	

If we cast a glance at the comparative statistic loss functions, such as RMSE,MAE,MAPE and TIC the same indicator were at least on ARIMA(2,0,1) model [4].

Table.7. Statistic loss functions of the models.				
Tests	**ARIMA(2,0,1)**	**ARIMA(6,0,1)**	**ARIMA(5,0,4)**	**SARIMA(1,0,1)(0,0,1)x12**
RMSE	0,4111	0,549	0,5518	0,4865
MAE	0,3418	0,4711	0,4893	0,395
MAPE	0,3406	0,4694	0,4873	0,3931
TIC	0,00205	0,0027	0,0027	0,0024
Bias proportion	0,075	0,041	0,087	0,039

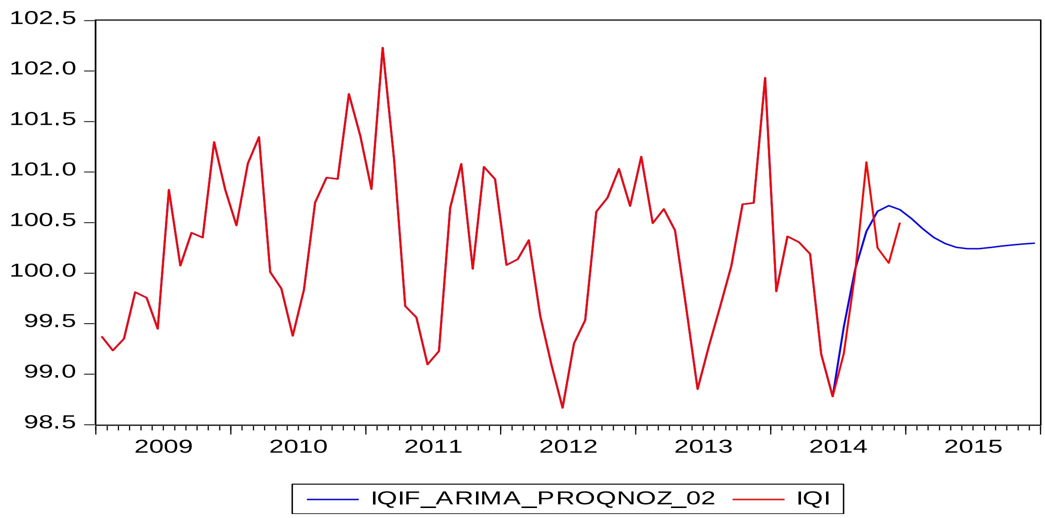
While analyzing the statistic loss functions RMSE,MAE,MAPE and TIC the figures were the least were at least on ARIMA(2,0,1).

Graph.7. ARIMA(2,0,1) model statistics loss functions



Stationarity were tested and test results is sufficiently significant.(See.Annex1.Table.8.)

Graph.8. Inflation dynamics on the model ARIMA(2,0,1)



There are two purposes in developping the significant econometric model. At first, fulfiling the analyses, the second is to forecast. In order to forecast on the model it needs additional statistic characteristics [9].

ARIMA(2,0,1) forecasting econometric model is as follows:

$$P_t = 100.2926 + 1.3941P_{t-1} - 0.5863P_{t-2} - 0.7830\epsilon_{t-1} \quad (20)$$

[0.090057] [0.181354] [0.110206] [0.194569]

Coefficients value of the model within 95% confidence interval were given in the Annex1.(See.Annex.1.Table.9.)

Table.10. ARIMA model emprical results

Dövr	ARIMA Model CPI	SARIMA Model CPI	Actual CPI	ARIMA Deviation(+/-)	SARIMA Deviation(+/-)
2014M07	99,47	99,47	99,21	0,3	0,3
2014M08	100,03	100,03	99,99	0,0	0,0
2014M09	100,41	100,21	101,10	-0,7	-0,9
2014M10	100,61	100,44	100,25	0,4	0,2
2014M11	100,67	100,48	100,10	0,6	0,4
2014M12	100,63	101,11	100,50	0,1	0,6
2015M01	100,54	99,97			
2015M02	100,44	100,29			
2015M03	100,35	100,28			
2015M04	100,29	100,22			
2015M05	100,26	99,87			
2015M06	100,24	99,80			
2015M07	100,24	100,07			
2015M08	100,25	100,23			
2015M09	100,27	100,30			
2015M10	100,28	100,34			
2015M11	100,29	100,35			
2015M12	100,30	100,34			

4. Conclusion

Modelling the inflationary processes and forecasting the estimates are of great importance while developping the investment projects, indexation of wages, predetermining the macroeconomic policy and preventive measures. The advanced forecasting models such as SARIMA and ARIMA have been applied and achieved results in this study. For forecasting the inflation the empirical results have been obtained on the seasonal avtoregressive integrated moving average model SARIMA(1,0,1) (0,0,1)x12 and non-seasonal avtoregressive integrated moving average model ARIMA(2,0,1). Short-term inflation forecasting on these models show that yearly inflation rate for the next year will be single digit. Hence, forecasting using the above mentioned models predicts the price stability in the next year. This study assumes scientific and practical importance in determining the monetary policy in the economy.

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ANNEX.1.

Graph.2.Correlogram

Sample: 2009M01 2014M12						
Included observations: 72						
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |**** |	. |**** |	1	0.585	0.585	25.719	0.000
. |** |	.*| . |	2	0.289	-0.081	32.095	0.000
. | . |	.*| . |	3	0.070	-0.100	32.479	0.000
.*| . |	**| . |	4	-0.166	-0.226	34.630	0.000
***| . |	**| . |	5	-0.368	-0.239	45.417	0.000
***| . |	. | . |	6	-0.362	-0.002	56.009	0.000
***| . |	.*| . |	7	-0.353	-0.133	66.209	0.000
**| . |	. | . |	8	-0.266	-0.031	72.082	0.000
. | . |	. |*. |	9	-0.016	0.173	72.103	0.000
. |*. |	. | . |	10	0.154	0.029	74.146	0.000
. |*** |	. |** |	11	0.358	0.248	85.365	0.000
. |**** |	. |*. |	12	0.497	0.171	107.28	0.000
. |*** |	.*| . |	13	0.387	-0.097	120.78	0.000
. |*. |	.*| . |	14	0.142	-0.145	122.64	0.000
. | . |	.*| . |	15	-0.044	-0.101	122.82	0.000
**| . |	. | . |	16	-0.221	-0.038	127.48	0.000
**| . |	. | . |	17	-0.331	0.036	138.06	0.000
***| . |	.*| . |	18	-0.410	-0.165	154.65	0.000
***| . |	. | . |	19	-0.348	0.037	166.86	0.000
**| . |	.*| . |	20	-0.276	-0.107	174.64	0.000

.*| . |	.*| . |	21	-0.154	-0.142	177.13	0.000
. | . |	. | . |	22	0.007	-0.045	177.13	0.000
. |*. |	. | . |	23	0.176	-0.057	180.52	0.000
. |** |	. |*. |	24	0.310	0.093	191.17	0.000
. |** |	. | . |	25	0.307	0.037	201.85	0.000
. |*. |	.*| . |	26	0.176	-0.072	205.45	0.000
. | . |	. | . |	27	0.017	0.019	205.48	0.000
.*| . |	. | . |	28	-0.095	-0.033	206.58	0.000
**| . |	. | . |	29	-0.220	-0.051	212.58	0.000
**| . |	. | . |	30	-0.287	0.002	223.06	0.000
**| . |	. | . |	31	-0.257	-0.004	231.62	0.000
.*| . |	. |*. |	32	-0.171	0.084	235.52	0.000

Table.4. SARIMA (1, 0, 1) (0, 0, 1) x12 model stationarity test.

Null hypothsis: RESID01 has a unit root.			t-Statistic	Prob.*
Exogen: Constant				
ADF test statistics			-8.569225	0.0000
Critique value test:	1% level		-3.528515	
	5% level		-2.904198	
	10% level		-2.589562	

Table.8. ARIMA (2,0,1) model stationarity test.

Null hypothsis: RESID02 has a unit root.			t-Statistic	Prob.*
Exogen: Constant				
ADF test statistics			-8.811665	0.0000
Critique value test:	1% level		-3.528515	
	5% level		-2.904198	
	10% level		-2.589562	

ith 95% CI on parameters of model ARIMA(2,0,1)

Variable	Coefficients	Low	High
C	100.2926	100.1128	100.4724
AR(1)	1.394135	1.032049	1.756220
AR(2)	-0.586309	-0.806342	-0.366276
MA(1)	-0.783051	-1.171520	-0.394583