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Prediction of Inflation in Algeria using ARIMA Models

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ABSTRACT

This research uses annual time series data on inflation rates in Algeria from 1970 to 2017, to model and forecast inflation using ARIMA models. Diagnostic tests indicate that A is I(1). The study presents the ARIMA (1, 1, 1). The diagnostic tests further imply that the presented optimal ARIMA (1, 1, 1) model is stable and acceptable for predicting inflation in Algeria. The results of the study apparently show that A will ranging between 4.9% and 5.2% over the out-of-sample period. Monetary authorities in Algeria are expected to tighten Algeria's monetary policy in order to maintain price stability.

Key Words: Forecasting, Inflation

JEL Codes: C53, E31, E37, E47

INTRODUCTION

Inflation can be defined as the sustained increase in the general level of prices and services over time (Blanchard, 2000). There is a general consensus on the fact that inflation is harmful for growth in any economy. Inflation is one of the central terms in macroeconomics (Enke & Mehdiyev, 2014) simply because it harms the stability of the acquisition power of the national currency, affects economic growth because investment projects become riskier, distorts consuming and saving decisions, causes unequal income distribution and also results in difficulties in financial intervention (Hurtado *et al*, 2013). As the prediction of accurate inflation rates is a key component for setting the country's monetary policy, it is especially important for central banks to obtain precise values (Mcnelis & Mcadam, 2004). Economic agents, private and public alike; monitor closely the evolution of prices in the economy, in order to make decisions that allow them to optimize the use of their resources (Hector & Valle, 2002). Decision-makers hence need to have a view of the likely future path of inflation when taking measures that are necessary to reach their objective (Buelens, 2012). To avoid adjusting policy and models by not using an inflation rate prediction can result in imprecise investment and saving decisions, potentially leading to economic instability (Enke & Mehdiyev, 2014). In this study, we seek to model and forecast inflation in Algeria using ARIMA models.

LITERATURE REVIEW

Nyoni (2018) studied inflation in Zimbabwe using GARCH models with a data set ranging over the period July 2009 to July 2018 and established that there is evidence of volatility persistence for Zimbabwe's monthly inflation data. Nyoni (2018) also modeled inflation in Kenya using

ARIMA and GARCH models and relied on annual time series data over the period 1960 – 2017 and found out that the ARIMA (2, 2, 1) model, the ARIMA (1, 2, 0) model and the AR (1) – GARCH (1, 1) model are good models that can be used to forecast inflation in Kenya. Nyoni & Nathaniel (2019), based on ARMA, ARIMA and GARCH models; studied inflation in Nigeria using time series data on inflation rates from 1960 to 2016 and found out that the ARMA (1, 0, 2) model is the best model for forecasting inflation rates in Nigeria.

MATERIALS & METHODS

Box – Jenkins ARIMA Models

One of the methods that are commonly used for forecasting time series data is the Autoregressive Integrated Moving Average (ARIMA) (Box & Jenkins, 1976; Brocwell & Davis, 2002; Chatfield, 2004; Wei, 2006; Cryer & Chan, 2008). For the purpose of forecasting inflation rate in Algeria, ARIMA models were specified and estimated. If the sequence $\Delta^d A_t$ satisfies an ARMA (p, q) process; then the sequence of A_t also satisfies the ARIMA (p, d, q) process such that:

$$\Delta^d A_t = \sum_{i=1}^{p} \beta_i \Delta^d A_{t-i} + \sum_{i=1}^{q} \alpha_i \mu_{t-i} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[1]}$$

which we can also re – write as:

$$\Delta^d A_t = \sum_{i=1}^{p} \beta_i \Delta^d L^i A_t + \sum_{i=1}^{q} \alpha_i L^i \mu_t + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{[2]}$$

where Δ is the difference operator, vector $\beta \in \mathbb{R}^p$ and $\alpha \in \mathbb{R}^q$.

The Box – Jenkins Methodology

The first step towards model selection is to difference the series in order to achieve stationarity. Once this process is over, the researcher will then examine the correlogram in order to decide on the appropriate orders of the AR and MA components. It is important to highlight the fact that this procedure (of choosing the AR and MA components) is biased towards the use of personal judgement because there are no clear – cut rules on how to decide on the appropriate AR and MA components. Therefore, experience plays a pivotal role in this regard. The next step is the estimation of the tentative model, after which diagnostic testing shall follow. Diagnostic checking is usually done by generating the set of residuals and testing whether they satisfy the characteristics of a white noise process. If not, there would be need for model re – specification and repetition of the same process; this time from the second stage. The process may go on and on until an appropriate model is identified (Nyoni, 2018).

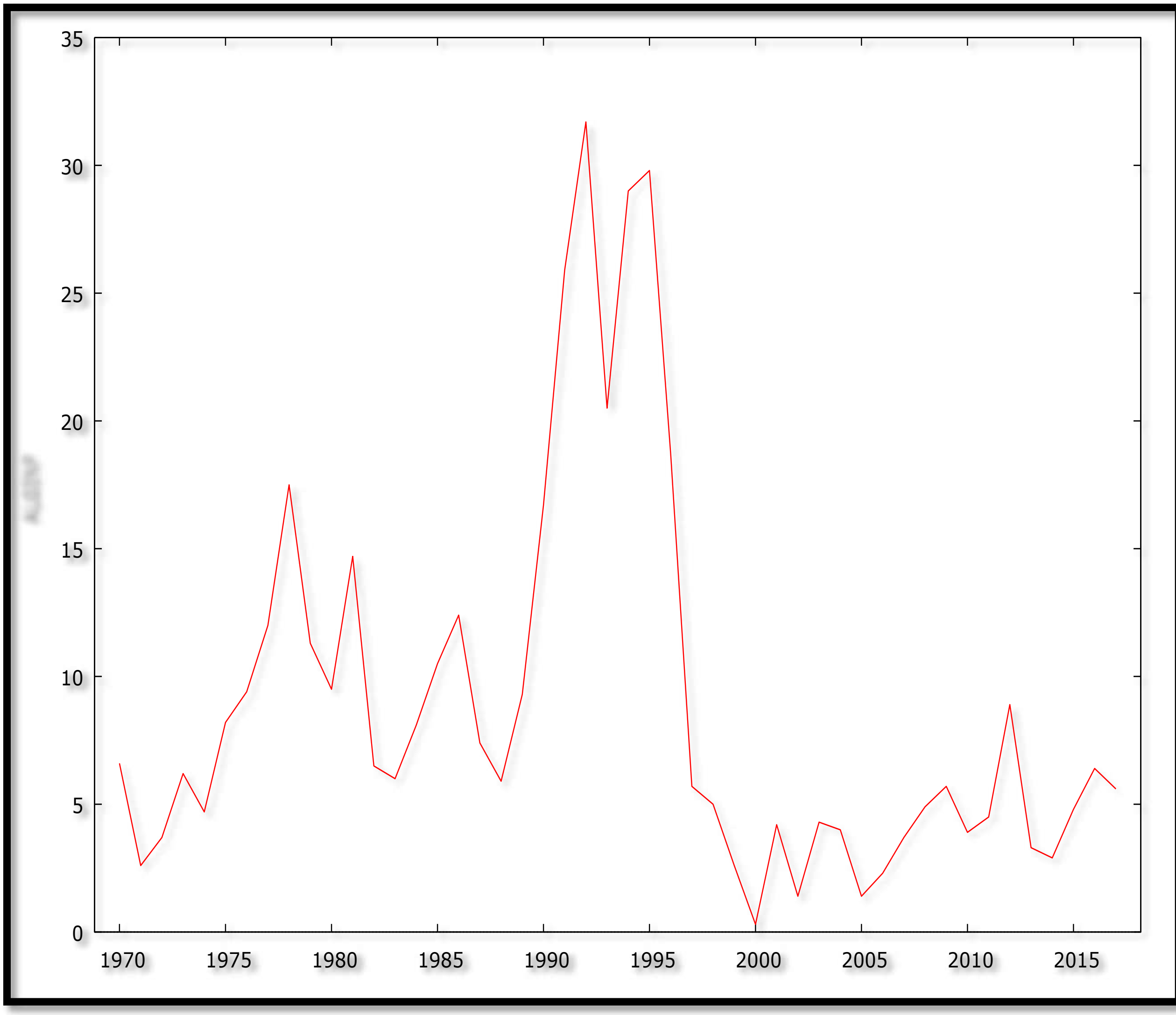
Data Collection

This study is based on a data set of annual rates of inflation in Algeria (ALGINF or simply A) ranging over the period 1970 – 2017. All the data was taken from the World Bank.

Diagnostic Tests & Model Evaluation

Stationarity Tests: Graphical Analysis

Figure 1



The Correlogram in Levels

Autocorrelation function for ALGINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 1

LAG	ACF	PACF	Q-stat. [p-value]
1	0.8079 ***	0.8079 ***	33.3336 [0.000]
2	0.5994 ***	-0.1536	52.0809 [0.000]
3	0.4524 ***	0.0525	62.9958 [0.000]

4	0.2573 *	-0.2632 *	66.6075 [0.000]
5	0.0717	-0.0799	66.8947 [0.000]
6	-0.0691	-0.0835	67.1673 [0.000]
7	-0.1643	0.0050	68.7469 [0.000]
8	-0.1602	0.1795	70.2877 [0.000]
9	-0.1395	-0.0342	71.4855 [0.000]

The ADF Test in Levels

Table 2: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-2.158520	0.2237	-3.577723	@1%	Non-stationary
			-2.925169	@5%	Non-stationary
			-2.600658	@10%	Non-stationary

Table 3: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-2.270035	0.4413	-4.165756	@1%	Non-stationary
			-3.508508	@5%	Non-stationary
			-3.184230	@10%	Non-stationary

Table 4: without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-1.393976	0.1498	-2.615093	@1%	Non-stationary
			-1.947975	@5%	Non-stationary
			-1.612408	@10%	Non-stationary

Figure 1 and tables 1 – 4 show that A is non-stationary in levels.

The Correlogram (at 1st Differences)

Autocorrelation function for d_ALGINF ***, **, * indicate significance at the 1%, 5%, 10% levels.

Table 5

LAG	ACF	PACF	Q-stat. [p-value]
1	0.0371	0.0371	0.0691 [0.793]
2	-0.1653	-0.1669	1.4669 [0.480]
3	0.1265	0.1441	2.3047 [0.512]
4	-0.0272	-0.0733	2.3443 [0.673]

5	-0.0925	-0.0418	2.8137 [0.729]
6	-0.1322	-0.1674	3.7956 [0.704]
7	-0.2587 *	-0.2713 *	7.6498 [0.364]
8	-0.0262	-0.0468	7.6903 [0.464]
9	0.0725	0.0080	8.0088 [0.533]

ADF Test in 1st Differences

Table 6: 1st Difference-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-6.439798	0.0000	-3.581152	@1%	Stationary
			-2.926622	@5%	Stationary
			-2.601424	@10%	Stationary

Table 7: 1st Difference-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-6.401865	0.0000	-4.170583	@1%	Stationary
			-3.510740	@5%	Stationary
			-3.185512	@10%	Stationary

Table 8: 1st Difference-without intercept and trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
A	-6.512031	0.0000	-2.616203	@1%	Stationary
			-1.948148	@5%	Stationary
			-1.612320	@10%	Stationary

Tables 5 – 8 show that A is an I (1) variable.

Evaluation of ARIMA models (without a constant)

Table 9

Model	U	ME	MAE	RMSE	MAPE
ARIMA (1, 1, 1)	**0.69431**	-0.027781	3.4227	4.6209	54.183
ARIMA (1, 1, 0)	1.0211	-0.02112	3.5136	4.7116	67.133
ARIMA (0, 1, 1)	1.0309	-0.02116	3.4966	4.7098	66.753
ARIMA (2, 1, 1)	0.81352	-0.027394	3.4002	4.5954	58.691
ARIMA (1, 1, 2)	0.72084	-0.02965	3.379	4.5996	56.427

Theil's U must lie between 0 and 1, of which the closer it is to 0, the better the forecast method (Nyoni, 2018). The study will only consider the AIC as the criteria for choosing the best model for forecasting inflation in Algeria and therefore, the ARIMA (1, 1, 1) model is eventually selected.

95% Confidence Ellipse & 95% 95% Marginal Intervals

Figure 2 [AR (1) & MA (1) components]

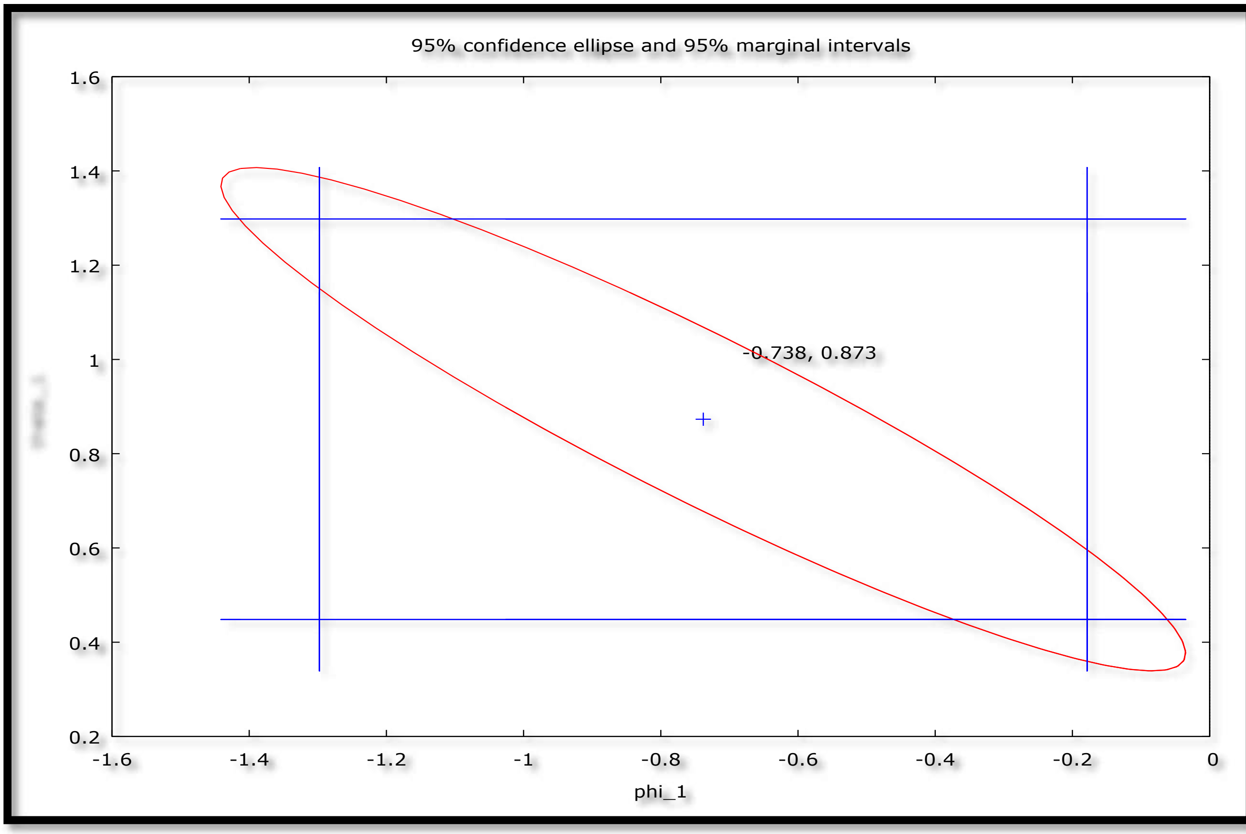


Figure 2 indicates that the accuracy of our forecast is satisfactory since it falls within the 95% confidence interval.

Residual & Stability Tests

ADF Tests of the Residuals of the ARIMA (1, 1, 1) Model

Table 10: Levels-intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.916508	0.0000	-3.584743	@1%	Stationary
			-2.928142	@5%	Stationary
			-2.602225	@10%	Stationary

Table 11: Levels-trend & intercept

Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.874012	0.0000	-4.175640	@1%	Stationary
			-3.513075	@5%	Stationary
			-3.186854	@10%	Stationary

Table 12: without intercept and trend & intercept

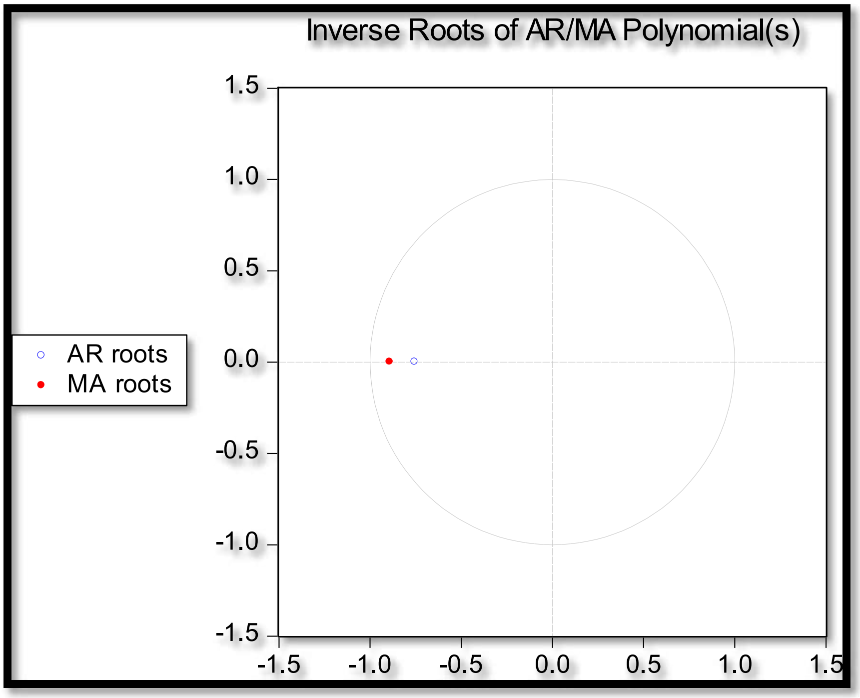
Variable	ADF Statistic	Probability	Critical Values		Conclusion
R_t	-6.996662	0.0000	-2.617364	@1%	Stationary
			-1.948313	@5%	Stationary

		-1.612229	@10%	Stationary

Tables 10, 11 and 12 show that the residuals of the ARIMA (1, 1, 1) model are stationary and hence the ARIMA (1, 1, 1) model is suitable for forecasting inflation in Algeria.

Stability Test of the ARIMA (1, 1, 1) Model

Figure 3



Since the corresponding inverse roots of the characteristic polynomial lie in the unit circle, it illustrates that the chosen ARIMA (1, 1, 1) model is stable and suitable for predicting inflation in Algeria over the period under study.

FINDINGS

Descriptive Statistics

Table 13

Description	Statistic
Mean	8.9708
Median	6.1
Minimum	0.3
Maximum	31.7
Standard deviation	7.6691
Skewness	1.5909
Excess kurtosis	1.7802

As shown above, the mean is positive, i.e. 8.9708%. The minimum is 0.3% and the maximum is 31.7%. The skewness is 1.5909 and the most striking characteristic is that it is positive, indicating that the inflation series is positively skewed and non-symmetric. Excess kurtosis was found to be 1.7802; implying that the inflation series is not normally distributed.

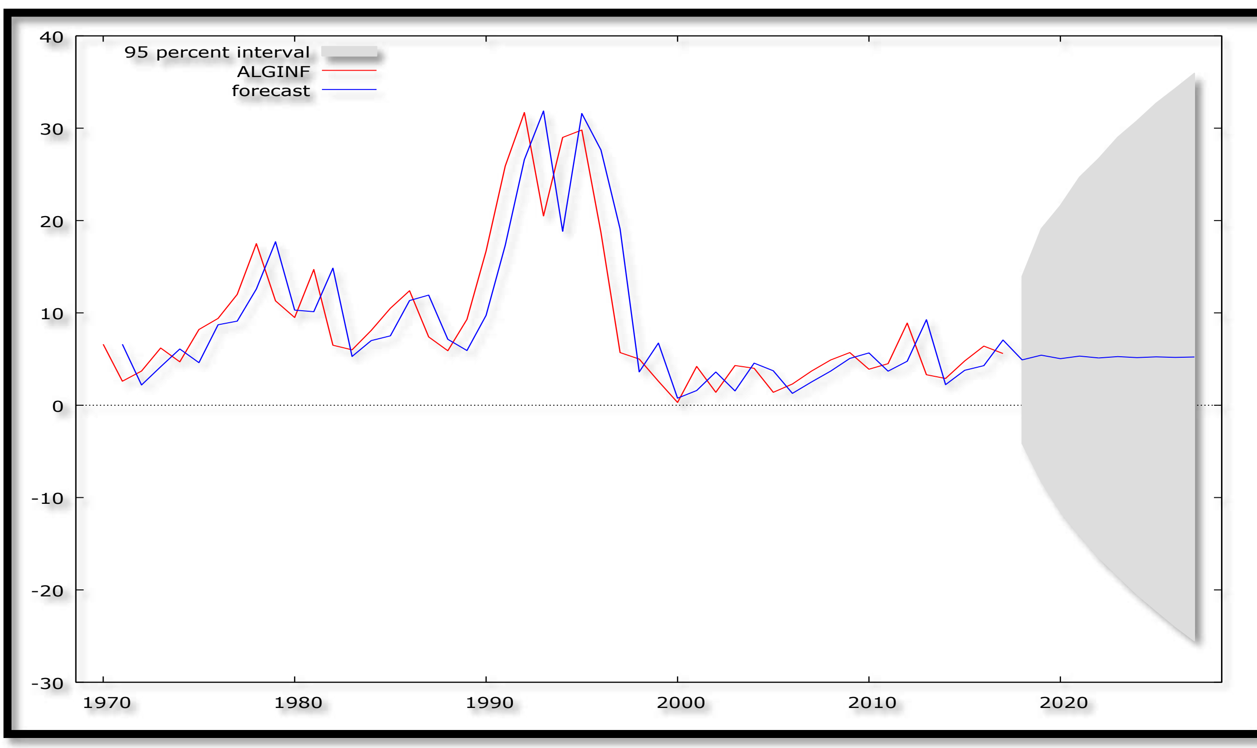
Results Presentation[1]

Table 14

ARIMA (1, 1, 1) Model: $\Delta A_{t-1} = -0.73812\Delta A_{t-1} + 0.873156\mu_{t-1}$ ……………………………………………………. [3] P: (0.0079) (0.0000) S. E: (0.2778) (0.2110)				
Variable	Coefficient	Standard Error	z	p-value
AR (1)	-0.738120	0.277796	-2.657	0.0079***
MA (1)	0.873156	0.210958	4.139	0.0000***

Forecast Graph

Figure 4



Predicted Annual Inflation in Algeria

Table 15

[1] *The *, ** and *** means significant at 10%, 5% and 1% levels of significance; respectively.*

Year	Prediction	Std. Error	95% Confidence Interval
2018	4.9	4.62	-4.1 - 14.0
2019	5.4	6.98	-8.3 - 19.1
2020	5.0	8.46	-11.5 - 21.6
2021	5.3	9.89	-14.1 - 24.7
2022	5.1	11.03	-16.5 - 26.7
2023	5.3	12.13	-18.5 - 29.0
2024	5.2	13.09	-20.5 - 30.8
2025	5.2	14.02	-22.2 - 32.7
2026	5.2	14.86	-24.0 - 34.3
2027	5.2	15.68	-25.5 - 36.0

Table 15, with a forecast range from 2018 – 2027; clearly show that inflation in Algeria is projected to be hovering, generally, around 5.2% in the next 10 years. This confirms the notion that the current price stability is set to continue prevailing in Algeria.

CONCLUSION

The ARIMA model was employed to investigate annual inflation rates in Algeria from 1970 to 2017. The study planned to forecast inflation in Algeria for the upcoming period from 2018 to 2027. The ARIMA (1, 1, 1) model is stable and most suitable model to forecast inflation in Algeria for the next ten years. Based on the results, policy makers in Algeria should continue to engage proper economic policies in order to fight against persistent inflationary pressures. Algerian policy makers are encouraged to consider tightening their monetary policy in order to foster macroeconomic stability in the country.

REFERENCES

[1] Blanchard, O (2000). Macroeconomics, 2nd Edition, *Prentice Hall*, New York.

[2] Box, G. E. P & Jenkins, G. M (1976). Time Series Analysis: Forecasting and Control, *Holden Day*, San Francisco.

[3] Brocwell, P. J & Davis, R. A (2002). Introduction to Time Series and Forecasting, *Springer*, New York.

[4] Buelens, C (2012). Inflation modeling and the crisis: assessing the impact on the performance of different forecasting models and methods, *European Commission*, Economic Paper No. 451.

[5] Chatfield, C (2004). The Analysis of Time Series: An Introduction, 6th Edition, *Chapman & Hall*, New York.

[6] Cryer, J. D & Chan, K. S (2008). Time Series Analysis with Application in R, *Springer*, New York.

[7] Enke, D & Mehdiyev, N (2014). A Hybrid Neuro-Fuzzy Model to Forecast Inflation, *Procedia Computer Science*, 36 (2014): 254 – 260.

[8] Hector, A & Valle, S (2002). Inflation forecasts with ARIMA and Vector Autoregressive models in Guatemala, *Economic Research Department*, Banco de Guatemala.

[9] Hurtado, C., Luis, J., Fregoso, C & Hector, J (2013). Forecasting Mexican Inflation Using Neural Networks, *International Conference on Electronics, Communications and Computing*, 2013: 32 – 35.

[10] Mcnelis, P. D & Mcadam, P (2004). Forecasting Inflation with Think Models and Neural Networks, *Working Paper Series*, European Central Bank.

[11] Nyoni, T & Nathaniel, S. P (2019). Modeling Rates of Inflation in Nigeria: An Application of ARMA, ARIMA and GARCH models, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 91351.

[12] Nyoni, T (2018). Modeling and Forecasting Inflation in Kenya: Recent Insights from ARIMA and GARCH analysis, *Dimorian Review*, 5 (6): 16 – 40.

[13] Nyoni, T (2018). Modeling and Forecasting Inflation in Zimbabwe: a Generalized Autoregressive Conditionally Heteroskedastic (GARCH) approach, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88132.

[14] Nyoni, T (2018). Modeling Forecasting Naira / USD Exchange Rate in Nigeria: a Box – Jenkins ARIMA approach, *University of Munich Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 88622.

[15] Nyoni, T. (2018). Box – Jenkins ARIMA Approach to Predicting net FDI inflows in Zimbabwe, *Munich University Library – Munich Personal RePEc Archive (MPRA)*, Paper No. 87737.

[16] Wei, W. S (2006). Time Series Analysis: Univariate and Multivariate Methods, 2nd Edition, Pearson Education Inc, Canada.