JOURNAL OF SMART ECONOMIC GROWTH
www.jseg.ro ISSN: 2537-141X Volume 5, Number 2, Year 2020

FORECASTING ALGERIAN GDP USING ADAPTIVE NEURO FUZZY INFERENCE SYSTEM DURING THE PERIOD 1990-2019

Abdelkader Sahed[1], Hacen Kahoui[2], Mohammed Mekidiche[3]
[1,2,3] Faculty of Economics, University Centre of Maghnia, Maghnia, Algeria
sahed14@yahoo.fr [1], hacenkahwi@gmail [2], mkidiche@yahoo.fr [3]

Abstract: *In this research, two different models, i.e. adaptive-network-based fuzzy inference system (ANFIS) and autoregressive integrated moving average (ARIMA) were used to predict the quarterly GDP in Algeria during the period 1990 to 2019. The comparison shows that the ANFIS1 model provides better accuracy than the ARIMA(1,1,1) model in the quarterly forecast of GDP in Algeria. This is based on the quality prediction criterion of Root Mean Square Error (RMSE).*

JEL classification: C_{22}, C_{45}, E_{01}

Key words: GDP, Forecasting, ANFIS, ARIMA, Algeria

1. INTRODUCTION

The gross domestic product (GDP) includes everything that has been produced locally, whether by using the services of production elements owned by citizens or by foreigners. GDP can be measured in three ways, the approach to expenditure, the approach to production and the approach to income (Abonazel and Abd-Elftah, 2019).

Gross domestic product is one of the most important factors that enables investors to assess the state's economic situation and thus to take an investment decision or to refrain from doing so, given the particular importance of the gross product in the economic climate, which played the most important role in bringing investment to the country (Jagannathan, 2019).

It is important to remember that some forecasting techniques can be imprecise, so we urgently need to approach them with extreme caution. Among the leading methods in the field of GDP forecasting, we find linear time-series methods (Box Jenkins method) first developed in Box and Jenkins (1976), known as the ARIMA (Auto-Regressive-Integrated-Moving Average) methodology (Dritsaki , 2015) Hybrid methods that combine fuzzy logic and neural networks are called the Adaptive Neuro Fuzzy Inference System method.

The aim of this paper is to compare the linear and non-linear model of Algerian GDP forecasts in 1990 and 2019 defined in ARIMA and the ANFIS model respectively. Experiments for both the ARIMA and ANFIS models show how these models fit into Algeria's GDP.

The article is divided as follows, the literature review is discussed following the introduction. I'll offer an overview of the data sources used in the next section. ARIMA Model, ANFIS model, study and findings are discussed in the next section afterwards. Lastly, the section on conclusion completes the article 's key structure.

2. LITERATURE REVIEW

(Eissa, 2020) used the Box-Jenkins Autoregressive-Integrated Average (ARIMA) model for the Egyptian and Saudi economies, using annual time series data to estimate GDP per capita. The model fitted with ARIMA was evaluated for estimating Egypt and Saudi Arabia's GDP per capita over the next ten years. The findings indicate that ARIMA (1,1,2) and ARIMA (1,1,1,1) are respectively the most accurate statistical model for Egypt and Saudi Arabia, as predicted in previous literature. Diagnostic tests show that the two models, presented separately, are consistent and predictable.

(Ramandeep et al, 2020), They tried to predict gross domestic product (GDP) by applying the Box Jenkins forecasting method. For thirty-seven years the data were collected and attempts were made to construct a predictive GDP model using the Autoregressive-Integrated Moving Average (ARIMA) model. For thirty-seven years from 1980 to 2017, ARIMA (1, 1 , 7) model has been used to figure the GDP.

(Sunitha et al, 2018), The aim of their studies is to estimate GDP growth. from past experience, it is clear that there has been cyclical volatility in the GDP economy. The Autoregressive Moving Average and Artificial Neural Network (ANN) are among the many common prediction models. ARIMA Model and the ANN model were estimated for a mean root square (RMSE) error and a mean absolute relative error (MAPE). In particular, both models are compared with RMSE and MAPE, and it can be seen from analyzes that ANN performs better than conventional, that is to say, statistical models. ARIMA.

(Yang et al, 2018), The goal of their study is to predict GDP in Macao on a quarterly basis using different models of the neural network. The lack of determining economic factors and the lack of economic data make this a challenge. Forecast errors were compared in three separate neural network templates including Back Propagation (BP), Elman and Radial Base Function (RBF). Elman was never used in literature in the GDP forecasting, but Elman's recent topology in the network, which can remember historical economic details, makes the error forecast loss.

(Vrbka, 2016), Their paper aimed to forecast eurozone countries' GDP growth until the year 2025. It was decided the RBF 1-10-1 network was the strongest. It can be seen that the most effective method for forecasting GDP appears in the RBF models.

3. MATERIALS AND METHODS

3.1. Data Selection and Processing

This paper examines GDP data for the quarterly period from 1990 to 2019. The GDP data was obtained from the official website (http: /www.ons.dz/). Both data analysis and forecasting of GDP data is performed using the program R and Matlab.

3.2. ARIMA Models

Box and Jenkins (1976) have made ARIMA models more popular. the ARIMA model is a basic but popular approach to time series forecasting. two forms of linear regressions are used in the development of the ARIMA model, the Autoregressive (AR) is written in the following:

$$y_t = \theta_0 + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} \tag{1}$$

and the Moving Average (MA) is written as follows:

$$y_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \cdots + \phi_q \varepsilon_{t-q} \tag{2}$$

Through incorporating these models with the same data, the form ARIMA becomes as follows:

$$y_t = \theta_0 + \theta_1 y_{t-1} + \cdots + \theta_p y_{t-p} + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \cdots + \phi_q \varepsilon_{t-q} \tag{3}$$

Time series data stationarity is a requirement for ARMA models, which implies that mean and variance are constant over time. If this condition is not met, the data should be transformed to stationary data by way of differences (Al-Musaylh et al, 2018).

When the time series data are stationary, the next estimate shall be "p" and "q." For parameter identification, autocorrelation and partial autocorrelation and the Akaike Information Criterion (AIC) may be used (Zhang et al, 2018).

After the identification process, we proceed to the estimate of the model parameters, which is defined by the maximum likelihood method, and diagnosis, The last step is creating the forecasting models (Zhang et al, 2018).

3.3. Adaptive Neuro-Fuzzy Inference System

Jang first suggested the Adaptive Neuro Fuzzy Inference System (ANFIS), 1993, it is a hybrid of the Artificial Neural Network (ANN) and the Fuzzy Inference System (FIS) (Sari et al, 2017).

Fuzzy Set and Fuzzy Inference Systems are the technical terms used in ANFIS modeling. Input space is transformed by a function named membership function into a given weight or degree of membership. Membership function defines how to convert and point in the input space into membership weights or degrees between 0 and 1. In this analysis, There are two types more widely used of membership functions, namely Gaussian and Trianguler (Faulina et al, 2012).

A basic ANFIS system is shown in fig. 1. For the sake of simplification we assumed that two Takagi and sugeno rules were based on two x and y inputs, which could be described as (Awan and Bae, 2013):

$$Rule\,1: if\ x\ is\ A_1\ and\ y\ is\ B_1,\ then\ f_1 = p_1x + q_1y + r_1$$

$$Rule\,2: if\ x\ is\ A_2\ and\ y\ is\ B_2,\ then\ f_2 = p_2x + q_2y + r_2$$

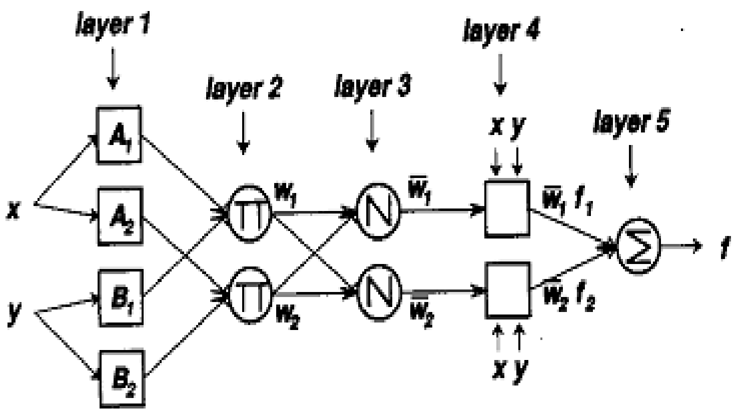

Fig.1- ANFIS structure

Source: (Jang, 1993)

There are five layers in the ANFIS network. The node function defines several different nodes in each layer (Catalão et al, 2011; Jang, 1993).

Layer 1: In this layer, every node i is a square node with a node function.

$$O_i^1 = \mu_{A_i}(x) \tag{4}$$

Layer 2: In this layer, each node is a circle node named Π which multiplies the input and sends the out product. Out product. For illustration.

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y),\ i = 1, 2. \tag{5}$$

Layer 3: Each node is labeled N in this layer. The ith node calculates the ratio of firing strength of the ith rule to the sum of the firing strengths of all rules:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2},\ i = 1, 2. \tag{6}$$

Layer 4: In this layer,. node i is a square node with a node function

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{7}$$

Layer 5: In this layer , the single node is a circle node labeled C which calculates the total output for all the input signals.

$$O_1^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

3.4. Forecast performance statistics

There are fairly common criteria used for determining the validity of out-of-sample predictions. x is the real observation, and $\hat{x}$ the forecast. In the following (Tkacz and Hu, 1999).

Root mean squared error:

$$RMSE = \sqrt{\frac{\sum (x_i - \hat{x}_i)^2}{n}} \tag{9}$$

Mean absolute deviation:

$$MAD = \frac{\sum |x_i - \hat{x}_i|}{n} \tag{10}$$

The correlation coefficient:

$$r = \frac{\sum (x - \bar{x})(\hat{x} - \bar{\hat{x}})}{\sqrt{\left[\sum (x - \bar{x})^2 (\hat{x} - \bar{\hat{x}})^2\right]}} \tag{11}$$

4. RESULTS AND DISCUSSION

The time series that will be studied contains quarterly data representing the value of GDP for the period from 1990 to 2019, as shown in Figure 2.

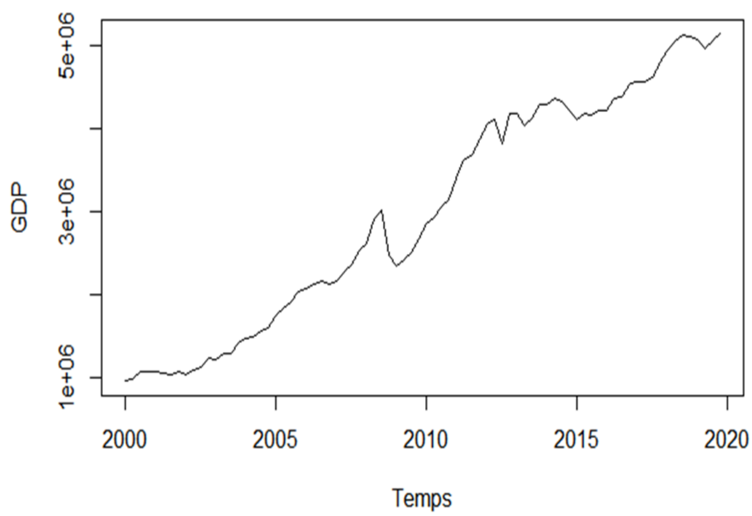

Fig.2- Time series plot of GDP in Algeria

JOURNAL OF SMART ECONOMIC GROWTH
JSEG
www.jseg.ro ISSN: 2537-141X Volume 5, Number 2, Year 2020

The previous figure indicates that GDP data has a trend, which means that the average is not constant and the variance is not constant, so the data has been transformed through the logarithm.

Firstly, the data were divided into 80% for training and 20% for testing. Table 1 shows the ADF, PP and KPSS stationarity test studies of the original LGDP series, We found that the adf, PP test's probability value is greater than 5 % , it is less than 5% for the kpss test, which means that the GDP series is non-stationary. Until we use the ARIMA model, GDP data must be converted into stationary data via a first order difference operation (see table 2).

Table 1. Stationarity Test of original series

Test	P-Value	Decision
ADF	0.909	non-stationary
PP	0.7348	non-stationary
KPSS	0.01	non-stationary

Table 2. Stationarity Test of 1st difference series

Test	P-Value	Decision
ADF	0.01	stationary
PP	0.01	stationary
KPSS	0. 1	stationary

Figure 3. indicates the simple and partial autocorrelation function of the series under study according to the first differences, the suggested models are ARIMA (0,1,1,1), ARIMA (1,1,1) and ARIMA (1,1 , 0).

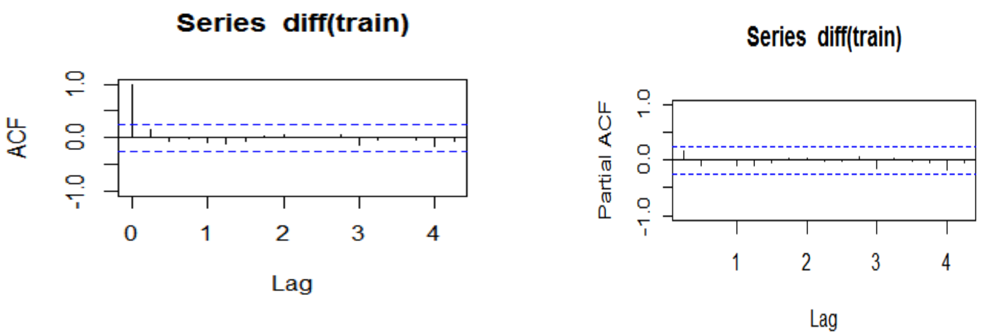

Fig.3- ACF and PACF plot of 1nd difference of GDP series

Table 3. Different ARIMA Models for GDP in Algeria

Model	AIC	Log likelihood
ARIMA(0,1,1)	-198.18	101.01
ARIMA(1,1,1)	-200.77	103.39
ARIMA(1,1,0)	-199.05	101.52

Table 3 shows that ARIMA(1,1,1) can obtain the lowest AIC criterion value and the highest log likelihood, so that ARIMA(1,1,1) can be relied on when modeling the GDP in Algeria. The maximum likelihood method results of ARIMA (1, 1, 1) model are shown in the following equation 12.

$$y_t = 0.9939 y_{t-1} + \varepsilon_t - 0.9476 \varepsilon_{t-1} \tag{12}$$

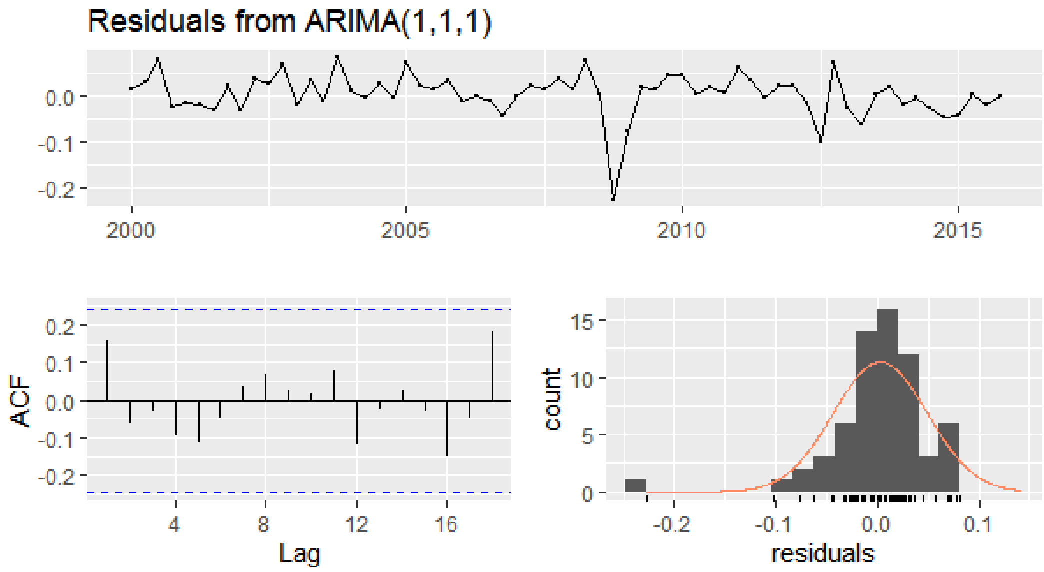

Fig.4- Correlogram plots of residuals of ARIMA (2, 2, 0) mode

According to figure 4. The Correlograms of residual arima (1,1,1) was found, and every diagram was not showing every noticeable spikes. The residual plot also demonstrates the suitability of the models and that there is no serial correlation where the probability value of Ljung box test is 0.6451 which is greater than 5%. The normal probability plot shows that ARIMA (1,1,1) residues are normally distributed. As a result, the ARIMA (1,1,1) was successfully chosen as the exact model for the prediction of GDP in Algeria.

To get the ANFIS model, we must set the input and output target. We use a significant delay based on the ARIMA models as an input variable. For example, in GDP series, there are three types of input, Y_{t-1} from the first model, Y_{t-1}, Y_{t-2} from the second model, Y_{t-1}, Y_{t-2}, Y_{t-3} from the third model.

Table 4 is the result of the accuracy of the forecast for each method.

For best forecasting, we use RMSE from Data set Training and Testing. Table 4 shows that the best model for GDP forecasts is ANFIS1 depending on the RMSE criterion.

Table 4. The results of models computed over the Training and Testing period

Model No.	Description	MF	Training RMSE	Testing RMSE
1	ANFIS1	Gauss	0.019017	0.021855
2	ANFIS2	Gauss	0.016226	0.05474
3	ANFIS3	Gauss	0.010117	0.049011
4	ARIMA(1,1,1)		0.046181	0.023262

Following figure 5. shows the actual against predicted values and shows that the observed value is approximately equal to forecast value. Hence we may confirm that the ANFIS1 model fits the GDP data properly.

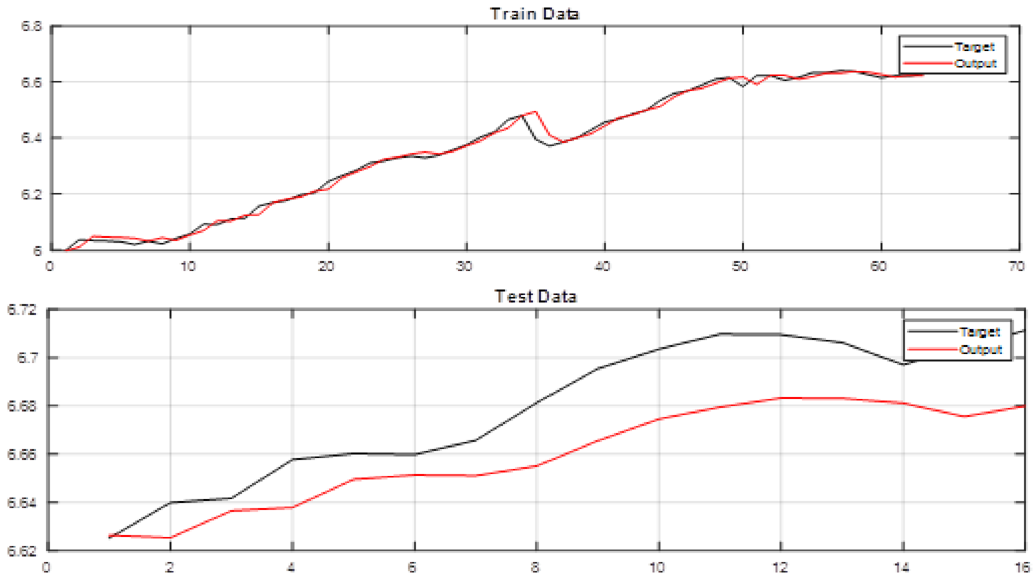

Fig.5- time series Plot of observed value vs predicted values

5. CONCLUSION

Due to the results and the interpretation, ANFIS1 is the best model in Algeria to forecast GDP. It uses a GAUSS Member Function, Yt-1 Input and a Degree of Membership as much as 2.

To give importance to the ANFIS1 model, it was compared with the ARIMA (1,1,1) model and it was found that the ANFIS1 model is the most fitting for forecasting of GDP in Algeria based on the RMSE forecast Accuracy criterion.

REFERENCES

1. Abonazel, M. R., & Abd-Elftah, A. I. (2019). Forecasting Egyptian GDP Using ARIMA Models. *Reports on Economics and Finance*, 5(1), 35-47.
2. Jagannathan, U. K. (2019). Arima Forecast for Indian Gdp. *Journal of Economics and Economic Education Research*, 20(3), 1-5.
3. Dritsaki, C. (2015). Forecasting real GDP rate through econometric models: an empirical study from Greece. *Journal of International Business and Economics*, 3(1), 13-19.
4. Eissa, N. (2020). Forecasting the GDP per Capita for Egypt and Saudi Arabia Using ARIMA Models. *Research in World Economy*, 11(1), 247-258.
5. Ramandeep Singh Arneja , Navdeep Kaur, and A.K. Saihjpal. (2020). Analyses and forecasting evaluation of GDP of India using ARIMA model. *International Journal of Advanced Science and Technology*, 29(11), 1102-1107.
6. Tkacz, G., & Hu, S. (1999). Forecasting GDP growth using artificial neural networks (No. 1999-3). *Bank of Canada*, p 21.
7. Sunitha.G, Sampath Kumar.K, JyothiRani.S. A, Haragopal.V. (2018). Forecasting GDP using ARIMA and Artificial Neural Networks Models under Indian Environment. *International Journal of Mathematics Trends and Technology* (IJMTT), 56(1), 60-70.
8. Yang, X., Zhang, Z., Cuthbert, L., & Wang, Y. (2018, June). Forecasting Macao GDP Using Different Artificial Neural Networks. *In International Conference on Information Science and Applications* (pp. 431-442). Springer, Singapore.
9. Vrbka, J. (2016). Predicting future GDP development by means of artificial intelligence. *Littera Scripta* [online], 9(3), 154-167.

10. Sari, N. R., Mahmudy, W. F., & Wibawa, A. P. (2017). Inflation Rate Forecasting Through Adaptive Neuro Fuzzy Inference System. *AICIT*, 8(1), 11-19.
11. Faulina, R., Lusia, D. A., Otok, B. W., & Kuswanto, H. (2012, September). Ensemble method based on anfis-arima for rainfall prediction. *In 2012 International Conference on Statistics in Science, Business and Engineering (ICSSBE)* (pp. 1-4). IEEE.
12. Awan, J. A., & Bae, D. H. (2013, September). Application of adaptive neuro-fuzzy inference system for dam inflow prediction using long-range weather forecast. *In Eighth International Conference on Digital Information Management* (ICDIM 2013) (pp. 247-251). IEEE.
13. Adyanti, D. A., Asyhar, A. H., Novitasari, D. C. R., Lubab, A., & Hafiyusholeh, M. (2017, September). Forecasts marine weather on java sea using hybrid methods: Ts-anfis. *In 2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)* (pp. 1-6). IEEE.
14. Catalão, J. P. S., Osório, G. J., & Pousinho, H. M. I. (2011, September). Application of an intelligent system based on EPSO and ANFIS to price forecasting. *In 2011 16th International Conference on Intelligent System Applications to Power Systems* (pp. 1-5). IEEE.
15. Al-Musaylh, M. S., Deo, R. C., Adamowski, J. F., & Li, Y. (2018). Short-term electricity demand forecasting with MARS, SVR and ARIMA models using aggregated demand data in Queensland, Australia. *Advanced Engineering Informatics*, 35, 1-16.
16. Zhang, L., Lin, J., Qiu, R., Hu, X., Zhang, H., Chen, Q., ... & Wang, J. (2018). Trend analysis and forecast of PM2. 5 in Fuzhou, China using the ARIMA model. *Ecological indicators*, 95, 702-710.
17. Jang, J. S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics*, 23(3), 665-685.