

Comparison of ARDL And Artificial Neural Networks Models for Foreign Direct Investment Prediction in Algeria

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Abstract:

This paper examined two common approaches, the ARDL model econometric technique and the artificial intelligence processes known as the artificial neural network model, which were applied to the forecasting process of FDI flows in Algeria from January 1990 to December 2019.

According to our empirical study, The time series were tested and found to be stationary in the first order, which would require the use of the cointegration test, and using the Bounds test, it was found that there was a long-run relationship between the variables. The ARDL model is estimated to perform the prediction.

Thereafter, the optimal neural network was designed, consisting of three nodes in the input layer and 12 nodes in the hidden layer. According to the Training algorithm, optimal weights and biases were determined, so that we could finally implement the prediction process, according to the MSE and RMSE prediction standards and found that the ANN model had better on the ARDL model in forecasting FDI flows in Algeria.

Keywords: Forecasting, ARDL, ANN, Algeria, FDI.

Jel Classification Codes : C53, B23, C45, E22.

ملخص:

تهدف هذه الورقة إلى المقارنة بين نهجين شائعين هما، أسلوب الاقتصاد القياسي ممثل في نموذج ARDL وأسلوب الذكاء الاصطناعي ممثل في نموذج الشبكة العصبية الاصطناعية، وهذا من أجل التنبؤ بتدفقات الاستثمار الأجنبي المباشر في الجزائر خلال الفترة من يناير 1990 إلى ديسمبر 2019. وفقاً لدراستنا التجريبية، تم اختبار السلاسل الزمنية ووجد أنها مستقرة من الدرجة الأولى، الأمر الذي يتطلب استخدام اختبار التكامل المشترك باستخدام اختبار Bounds، وجدنا أن هناك علاقة طويلة المدى بين المتغيرات. بالإضافة إلى تقدير نموذج ARDL لغرض إجراء عملية التنبؤ. بعد ذلك، تم تصميم الشبكة العصبية المثلى، والمكونة من ثلاث عقد في طبقة الإدخال و 12 عقدة في الطبقة المخفية. وفقاً لخوارزمية التدريب، تم تحديد الأوزان والتحيزات المثلى، ووفقاً لمعايير التنبؤ MSE و RMSE وجدنا أن نموذج ANN يعطي نتائج أفضل من نموذج ARDL في التنبؤ بتدفقات الاستثمار الأجنبي المباشر في الجزائر.

كلمات المفتاحية : التنبؤ، ARDL، ANN، الجزائر، الاستثمار الاجنبي المباشر.

تصنيف JEL : C53, B23, C45, E22.

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I. Introduction

Several more developing countries are attempting to attract foreign direct investment as a funding tool for economic and social growth, and it has become a significant objective for those nations with the goal of increasing national income and, as a result, raising real per capita income and living standards.

Foreign direct investment plays an significant role in economic growth, encourages domestic employment, raises work prospects, raises local currency demand, preserves market stability and increases Algeria's country's national income. Therefore, a environment for international investors must be established and the flow of foreign direct investments regulated (Tocar, S. 2018).

Therefore, we notice that the economic importance of FDI has risen in recent years, while FDI is poor in developing countries, yet there is high rivalry among developing countries for their share of FDI (Sara Zaitri, 2019).

According to the United Nations Trade and Development Conference (UNCTAD), the influx of FDI's into Algeria has been rising to 22% in 2018, with a total of \$1.5 trillion compared with a total of \$1.2 trillion in 2016, due to investment into the oil , gas and automobile industries (Xinhua, 2019).

In order to improve the business climate and attract foreign direct investment, Algeria relaxed limitations on non-strategic industries, as defined under rule 51/49 percent, in compliance with the Finance Act of 2020.

The advanced models of prediction thus play an important role in the accurate information obtained, in order to make decisions to draw foreign direct investment and to develop adequate strategic plans.

1.1 The problematic

In order to achieve the objective of this research, we ask the following main question: How effective is the suggested ANN method in predicting foreign investment flows compared to the ARDL approach?

In the same context, we propose the following hypotheses:

H1: The ARDL method achieves better results when forecasting foreign investment flows.

H2: The best results in forecasting foreign investment flows are obtained by using the ANN model.

1.2 Objective of the study

This study aims to forecast and predict foreign direct investment flows into Algeria over the next year in order to determine whether they are beneficial or not.

This study will also aid policymakers and scholars in determining what will happen to future foreign direct investment flows, as well as the future trend of foreign direct investment flows to Algeria, so that suitable economic policies may be implemented in accordance with the trend.

Furthermore, this study aims to fill a gap in the literature by forecasting foreign direct investment inflows into Algeria, as well as add to the existing knowledge (Ayodele Idowu, 2021).

1.3 The plan of the paper

The purpose of this study is to build and compare ARDL and Neural network models for the forecast of FDI flows for the country of Algeria and to identify the factors determining foreign direct investment (GDP, INF, EXR) in Algeria from 1990 to 2019.

In addition, the output comparison between the models described above used the predict accuracy criteria represented in the mean error squares (MSE) and the root error squares (RMSE).

The remainder of the study is structured as follows. The next Section includes the literature review, Section three contains the data and the methodology used, Section four introduces the results and discussion and finally study draws conclusion.

II. Literature review

(Perera, 2015) Studied the modeling and forecasting foreign direct investment (FDI) into SAARC for the period of 2013-2037 with ARIMA. They have found the FDI data is stationary according to the Augmented Dickey-Fuller Test. Their study identifies minimum AIC value and presents ARIMA (1, 1, 5) and ARIMA (1, 0, 5) models as optimal models to forecast FDI in the region. Box-Ljung test is used to illustrate the randomization of residuals.

An empirical investigation conducted by (Nyoni, 2018) at Box-Jenkins ARIMA approach to predicting net FDI inflows in Zimbabwe. They tested the stationarity of time series data from 1980 to 2017 for foreign investment flows, ADF test indicated that the FDI data is (I). The minimum AIC value indicates a better ARIMA(1,1,1) model for forecasting foreign direct investment in Zimbabwe. thus confirming its adequacy. A diagnosis of the inverse roots of AR / MA polynomials confirms that their model is stable. They determined that the predicted net FDI inflows over the next 2 decades show a relatively poor and unimpressive growth trend.

(Al-rawashdeh et al, 2011) used the Forecasting Foreign Direct Investment in Jordan for the Years (2011-2030). They implemented (ARIMA), models for the period from (1981-2010), and they got that the time series for the variable

(FDI) was not stationary in its levels during the time, and it suffers from a unit root, we have been working to make it stationary after identifying first order of difference which was used in (ARIMA) models. They used the computer program (Minitab, 14 and Eviews, 3.1) for data analysis and forecasting. The study of them reached a set of results and found out that the expected total volume of (FDI) inflows will reached (29207.06) million Jordanian dinar (JD) by the year 2030, while the average (FDI) is equal to (1479.096) million (JD) with an average annual growth of 3.22%.

(Jere et al, 2017) examined the Forecasting foreign direct investment to Zambia: a time series analysis. In this study, they compared three methods, Simple exponential smoothing (SES), Holt-Winters exponential smoothing (HWES) and autoregressive integrated moving average (ARIMA) .The best model is chosen to forecast annual FDI to Zambia for the period 1970 to 2014. They found that the ARIMA (1, 1, 5) that is most appropriate because it contains the minimum error.

III. Research Methodology

This section reviews data and the theoretical background for the methods used for forecasting of the Foreign Direct Investment in Algeria.

III.1 Variables and data

In this study, we are using FDI flows as dependent variable and the three variables are Gross domestic product, inflation rate and the official exchange as independent variables, which were determined based on economic theory and previous studies. The description of all the variables is as follows:

FDI: Foreign direct investment.

GDP: Gross domestic product.

INF: Inflation.

OEXR: Official exchange rate.

The annual data for the study variables were used for the period from 1990 to 2019 for the Algeria country. The data source is the World Development Indicator of the World Bank.

The mathematical structure of a model is centered on the following equation:

Foreign direct investment = f (Gross domestic product, Inflation, Official exchange rate)

While the econometric form of the above model is as follows (Eq. (1)):

$$FDI_t = B_0 + B_1GDP_t + B_2INF_t + B_3OEXR_t + \varepsilon_t \quad (1)$$

Where: B_0 is the intercept and B_1, B_2, B_3 are coefficients of independent variables, and ε_t is the error term.

III.2 The Autoregressive Distributed Lag (ARDL) Model

In ARDL, does not necessarily have to be the series stationary from the same order, as I (0) or I (1) or different. But it must not be integrated from order 2 and above (Rahman, M. et al. 2017).

First, the variables under study should be stationary, the Augmented Dickey-Fuller (ADF) unit root test methods were used for that.

The ARDL structure of Equations (1) transferred to equivalent general unrestricted error correction model (UECM) in Equatins (2):

$$\Delta FDI_t = B_0 + \sum_{i=1}^{n1} \beta_{1i} \Delta FDI_{t-i} + \sum_{i=0}^{n2} \beta_{2i} \Delta INF_{t-j} + \sum_{i=0}^{n2} \beta_{3i} OEXR_{t-k} + \theta_0 GDP_{t-1} + \theta_1 INF_{t-1} + \theta_2 OEXR_{t-1} + \varepsilon_t \quad (2)$$

Where:

ε_t : represent the white noise error terms

Δ : the first deifference operators

$n1, n2, n3$: represents lagged value

$\beta_1, \beta_2, \beta_3$: are error correction dynamics

$\theta_0, \theta_1, \theta_2$: represents the long run relationship among the variables in the model

Through equation (2), the bounds test method can be performed for the existence of cointegration relationships between variables, the null hypothesis is $H_0: \theta_1 = \theta_2 = \theta_3 = 0$ gainst the alternative is $H_1: \theta_1 \neq \theta_2 \neq \theta_3 \neq 0$ (Marques, A. et al. 2016).

To test the null hypothesis that there is no long-term relationship between the variants, Pesaran et al. (2001) developed two sets of critical values. Lower critical values refer to I(0), and upper critical values indicate I(1). If the value of F-test statistic is greater than the critical value I(1) we reject the null hypothesis, then there is a long-term relationship between the variables, If the value of F-test statistic is less than the critical value I(0) we accept the null hypothesis. If it falls between the boundaries of the critical values, the test is inconclusive (Jalae, S. A., et al. 2019).

In the case, the long run relationship between the study variables have been achieved.

The Parameters in the long run are estimated. the short run parameters for the variables can be found as follows (Eq.(3)):

$$\Delta FDI_t = B_0 + \sum_{i=1}^{n1} \beta_{1i} \Delta FDI_{t-i} + \sum_{i=0}^{n2} \beta_{2i} \Delta INF_{t-j} + \sum_{i=0}^{n2} \beta_{3i} OEXR_{t-k} + \eta_1 ECT_{t-1} + \varepsilon_t \quad (3)$$

Where:

ECT: represent the error correction term.

η_1 : represent the coefficient of error correction term.

If in the previous model there is a disturbance, The error correction term indicates how much time it will take to reach to its equilibrium path in the long run.

Finally, Cumulative Sum (CUSUM) and Cumulative Sum of Squares are used to check the stability of the coefficients in the short and long run to make sure of the quality of the model. (Ahmad, N., et al. 2017).

III.3 Artificial Neural Network Models

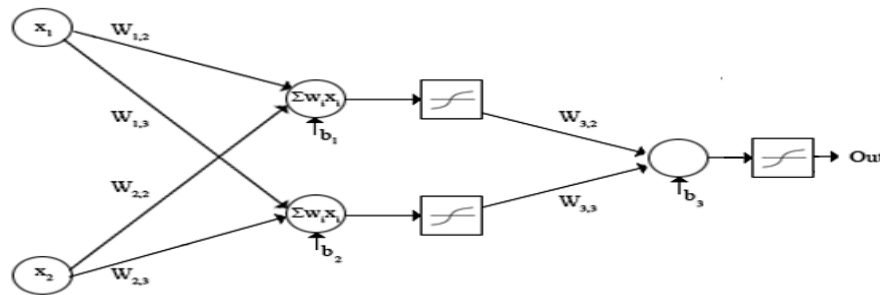
The Artificial neural networks had been inspired from the idea in calculating complex processes of the work of the human brain, as it has the ability to explain the nonlinear relationship between inputs and outputs, Whereas, the ANN has received great attention in the field of learning mechanisms by researchers in various subjects such as economics, statistics and engineering (Ramyar, et al. 2019).

There are different types of the ANN, in this study we are interested in MLP network, what's called back propagation network which consists of the input layer, the hidden layer and the output layer (Fig. 1), where the input layer nodes receive information from the independent variables and pass them to the hidden layer nodes by multiplying them by weights and adding biases, which they convert through the sigmoid nonlinear activation function. that pass to the output layer nodes, which turn it into via a linear activation function.

The MLP network needs to be trained for that, we use a training algorithm such as back propagation, cascade correlation and conjugate gradient. The primary goal of the training process is to reduce the overall error with adjusting weights and biases. (Kashaninejad, M., et al. 2009).

In addition, that determining the optimal number of neurons in the hidden layer is that it requires training the neural network several times for a different number of neurons in the hidden layer, and that the architectural selection for this network is based on the lowest mean square error (MSE) (Ramyar, et al. 2019) .

Fig. (01) : Multi layer perceptron neural network.



Source: (Vipul Lugade,. 2011)

IV. Results and Discussion

IV.1 ARDL Model

Stationarity test: At first, the Stationarity study for all variables under study is using the ADF test, where at the level, all variables are non- Stationary, for that we use the difference method and then we apply the ADF test on them, where it is clear from Table (01) that all the variables have become Stationary at first difference.

Table (01): ADF Test

Variables	ADF Test (level) Prob	ADF Test (1st difference) Prob	Decision
LFDI	0.2942	0.0014	I(1)
LGDP	0.391	0.0029	I(1)
LEXR	0.992	0.0000	I(1)
LINF	0.3229	0.0000	I(1)

Note: that all the variables were transformed into logarithmic form.

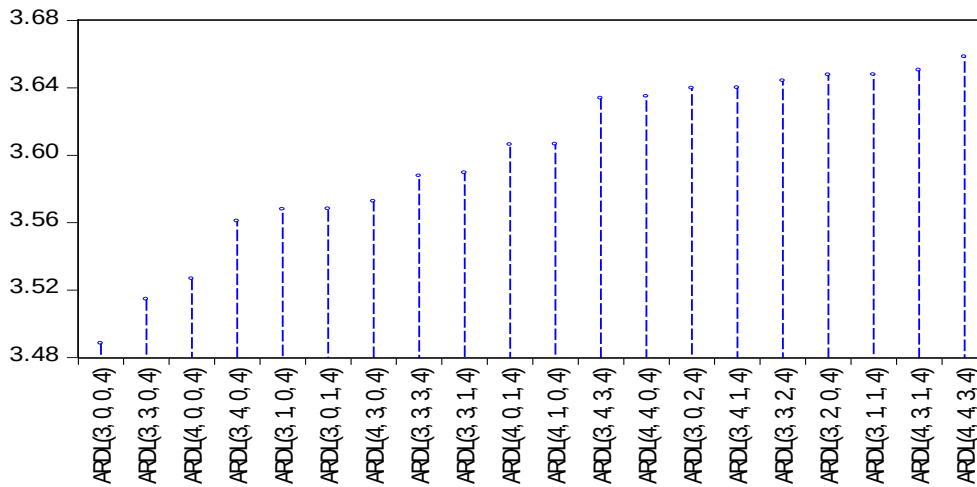
Source: Prepared by the researchers based on Eviews10 outputs

The ADF test results indicate that the Foreign direct investment, the Gross domestic, Inflation and the Official exchange rate are stationary in the first difference.

The Selection of ARDL Model: The ARDL models are identified statistical been using the Akaike information criteria for top 20 models, we found that the optimal lags are the ARDL (3,0,0,4) model (see Figure (02)).

Fig. (02) : Comparison of ARDL Models

Akaike Information Criteria (top 20 models)



Source: Prepared by the researchers based on Eviews10 outputs

After, the ARDL (3,0,0,4) model was identified, we used the EVIEWS 10 program to estimate the model and the results are shown in Table (02).

Table (02): The result of ARDL (3,0,0,4) model

Selected Model: ARDL(3, 0, 0, 4)	
Variable	Coefficient
LFDI(-1)	0.268370
LFDI(-2)	0.160043
LFDI(-3)	-0.408207
LGDP	0.228408
LINF	-0.124037
LEXR	0.069600
LEXR(-1)	-4.436943
LEXR(-2)	12.88474
LEXR(-3)	-15.96212
LEXR(-4)	10.93909
R-squared	0.941125
Adjusted R-squared	0.905801
Durbin-Watson stat	2.812347

Source: Prepared by the researchers based on Eviews10 outputs

Cointegration Test – ARDL Bounds Test: The cointegration test of (Pesaran et al, 2001) requires that the ARDL model be estimated beforehand.

The test statistic, Fisher's F-value, will be compared to the critical values (which form bounds). The results of the bounds cointegration test confirm the existence of a cointegration relationship between the series under study (the

value of F-stat is $>$ that of the upper bound), which makes it possible to estimate the long-term effects of GDP, INF and EXR on FDI (see Table (3)).

Table (03): Bounds cointegration test.

Test Statistic	Value	k
F-statistic	6.339745	3
Critical Value Bounds		
Significance	I0 Bound	I1 Bound
10%	2.01	3.1
5%	2.45	3.63
2.5%	2.87	4.16
1%	3.42	4.84

Source: Prepared by the researchers based on Eviews10 outputs

IV.2 ANN-MLP Model

The ANN model is used to forecast FDI inflows according to the following steps: (1) collecting data, (2) preprocessing data, (3) building the network, (4) train, and (5) test performance of model (Al Shamisi et al, 2011).

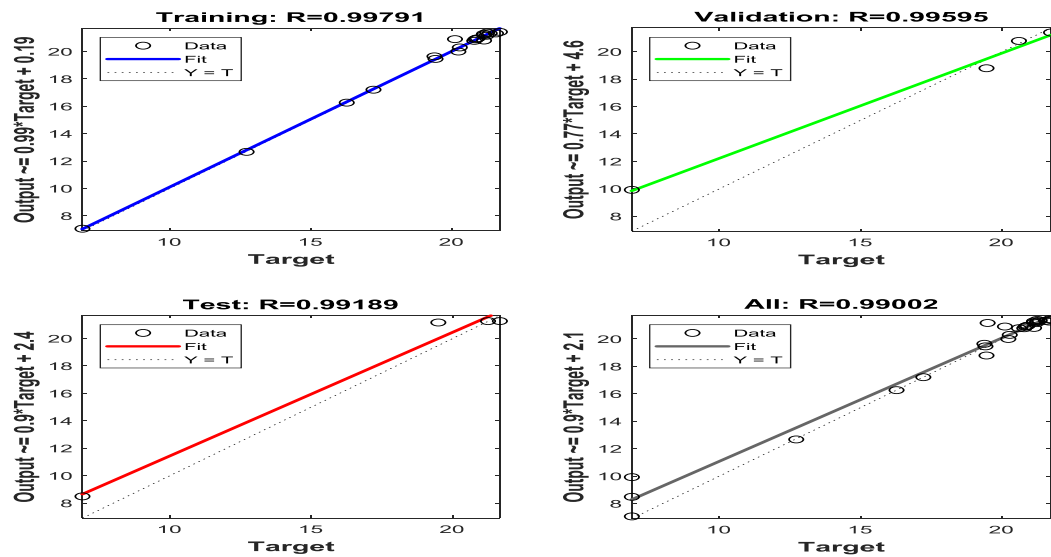
In the step of data collection, the target has been set represented in the variable of foreign direct investment, while the inputs are represented in the gross domestic product, inflation and the exchange rate of Algeria during the period 1990 to 2019.

At a data pre-processing step, the original data is converted into normalized data to eliminate the problem with units of measurement.

After that, the data was divided into three sections, the training group (70%), the validation group (15%) and the test group (15%).

Where in the design and training step of mlp neural networks, three layers have been used, the target layer contains the FDI variable and the input layer contains the variables (EXR, INF, GDP) while the number of nodes in the hidden layer has been determined by minimizing the Mean squared error and the strength of the correlation coefficient between the target variable and the output variable (see Figure (03)), 12 nodes are identified in the hidden layer, so the NETWORK final design is given by the following formula MLP(3-12-1) (see Figure (04)), In addition, the Sigmond non-linear activation function was used, choosing the 1000 epoch for network training and 0.001 rate error.

Fig. (03) : comparison between the real FDI and Predicted DFI



Source: Prepared by the researchers based on Matlab outputs

Once the optimal network weights and biases are obtained, the verification data is entered and compared with the target data in the verification step, in case the optimal network is not achieved. The weights and biases are adjusted until the optimal network is achieved.

The network is checked on entering the test data and using weights and biases Stored to confirm that the network has trained.

IV.3 Comparison of the Forecasting Residuals

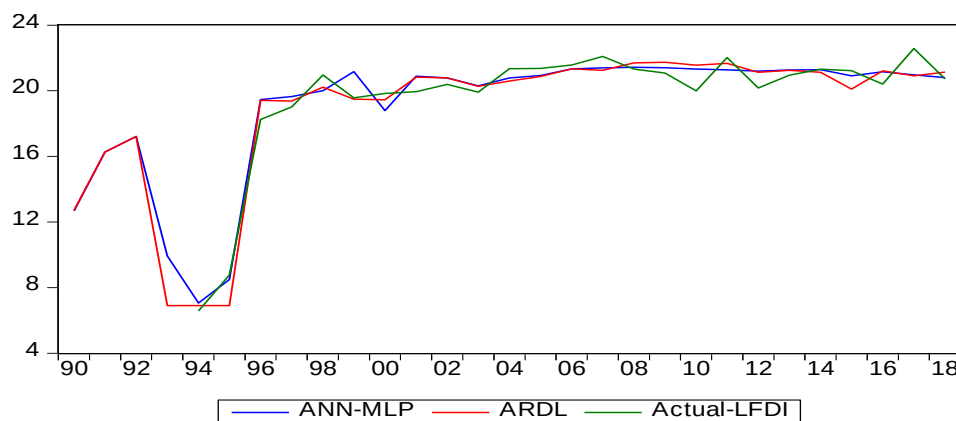
In order to prove the validity of the models used for the forecasting of foreign investment flows in Algeria, The mean square error (MSE) and the Root Mean Square Error (RMSE) were calculated. It is clear from the table (04) and the figure (4) that it is the neural network models that have the least errors in forecasting process, the ANNs outperformed ARDL in forecasting FDI. In fact, the ANN is characterized by its ability to estimate non-linear compounds present in time series.

Table (04): Comparison of the ANN-MLP and ARDL Models

	ANN-MLP	ARDL
MSE	0.560495033	0.699053818
RMSE	0.748662162	0.836094384

Source: Prepared by the researchers based on Matlab outputs

Fig. (04) : Comparison of the Actual Data, ANN-MLP and ARDL Models



Source: Prepared by the researchers based on Matlab outputs

V. Conclusion

In this study, we used two common approaches, the econometric technique known as the ARDL model and the artificial intelligence processes known as the artificial neural network model to be applied to the forecasting process of FDI flows in Algeria.

According to our empirical study, The time series were tested and found to be stationary in the first order, which would require the use of the cointegration test, and using the Bounds test, it was found that there was a long-run relationship between the variables. The ARDL model is estimated to perform the prediction.

Thereafter, the optimal neural network was designed, consisting of three nodes in the input layer and 12 nodes in the hidden layer. According to the Training algorithm, optimal weights and biases were determined, so that we could finally implement the prediction process, according to the MSE and RMSE prediction standards and found that the ANN model had better on the ARDL model in forecasting FDI flows in Algeria.

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