Numerical and Criteria Comparison between Box-Jenkins and Exponential Smoothing Methods in Short-term Forecasting

Abderrahmane Belguerna

Department of Mathematics and computer sciences, S.A University Center of Naama, Algeria.

Abstract: In this paper, we will compare two methods of forecasting a short-term time series, through several criteria such as Aic, Bic, MSE, log likelihood, j^2 and other. The first one of this two methods is the popular algorithm of Box-Jenkins and the second is the exponential smoothing method.

We are interested in the evolution over time of a phenomenon, in order to describe, explain and predict this phenomenon in the future. We have observations at different dates, ie a series of numerical values indexed by time.

For this, we will use R software. R is free software and programming language. It is very powerful for statistical methods, helps us to exploit the theoretical results obtained in the analysis of time series.

Keywords: Forecasting, Short-term, Box-Jenkins, Exponential smoothing, R software.

AMS Mathematics Subject Classification 2010 : 62M10, 97M10.

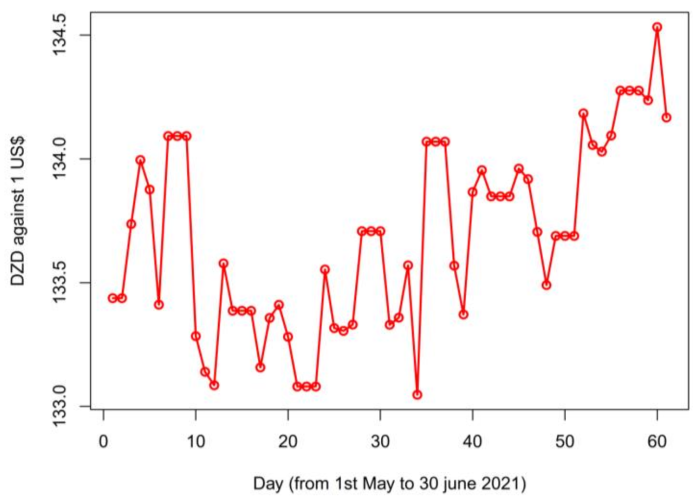
1. Introduction

The main purpose in this work is the comparison of two time series forecasting methods **(Granger, C., Newbold, P, 1976)**, the Box-Jenkins **(Box, G., Jenkins, G.M, 1976)** method and the simple exponential smoothing method **(Brockwell, P., Davis, R, 1996)** through a concrete example. For this, we will take in consideration the daily time series of the monetary exchange rate of one American $ against the Algerian Dinar **(World Bank, 2021)**. We have 61 observations from May 01, 2021 to June 30, 2021. To facilitate the calculations, we use R. R is a programming language and software, free and open-source, special and very powerful in statistical studies **(Hyndman, R.J., Khandakar, Y, 2008)**, **(Ljung, G., Box, G, 1978)**, **(Challis, R.E., Kitney, R.I, 1990)**. Using 50 observations for the estimate and we keep 11 observations to compare them with the values we are going to predict.

2.Data analysis

A visualization of our time series with the plot command of R language gives the following graph :

Figure.1 Exchange rate evolution of 1$ against Algerian Dinar (DZD)



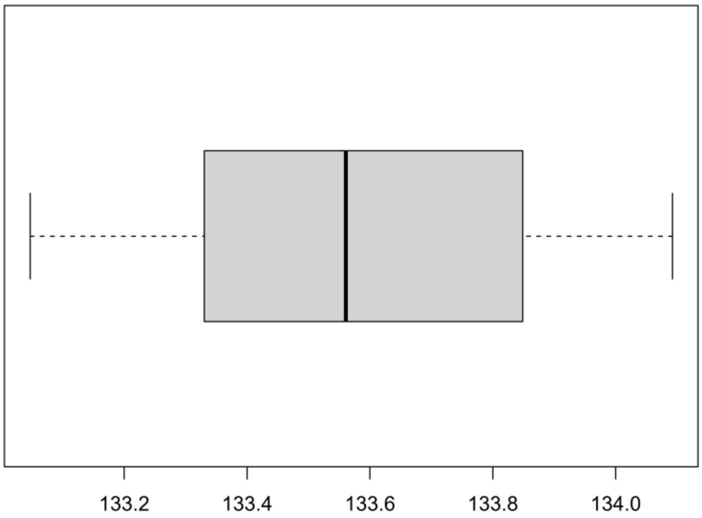
The command summary of R gives the following table

Table 1: Summary of the time series

Min	Q1	Median	Mean	Q3	Max
133	133.3	133.6	133.6	133.8	134.1

We run the boxplot command gives the following figure

Figure.2 Summary of the time series



3. Box-Jenkins method

G.BOX and G.JENKINS, in the seventies years contributed a lot in the theory and the practice of the models of the time series, the objective to which they propose to answer in their work. "Time Series Analysis, Forecasting and Control" is to build a random model of the ARMA allowing to best reproduce the realizations of a time series. The "auto.arima" function from the "forecast" library in R Returns the best ARIMA model for our time series according to either AIC, AICc or BIC value. The function conducts a search over a possible model within the order constraints provided. The "auto.arima()" function in R uses a variation of the Hyndman-Khandakar algorithm **(Hyndman, R.J., Khandakar, Y, 2008)**, which combines unit root tests, minimization of the AICc and MLE to obtain an ARIMA model. The arguments to "auto.arima()" provide for many variations on the algorithm.

Running the "auto.arima" function in R, we get the best selected model ARIMA (2, 0, 2) and estimated parameters, in the Table 2 below

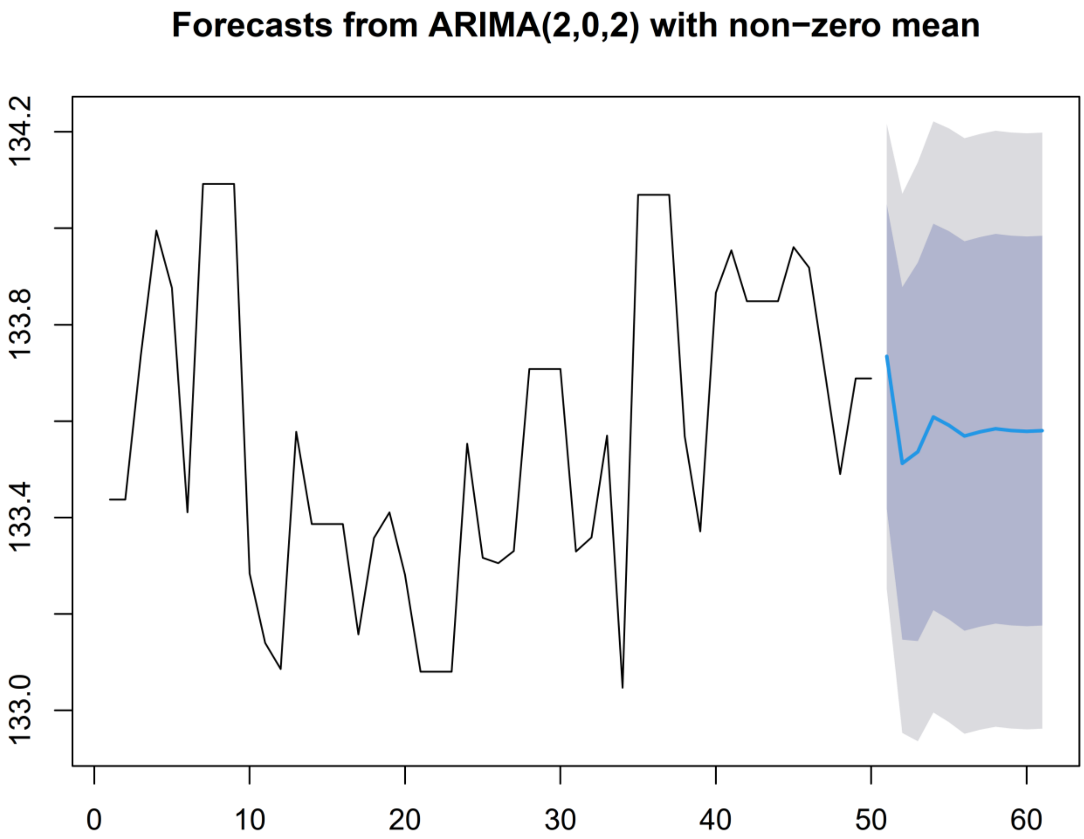
Table 2: Estimation of parameters

ar1	ar2	ma1	ma2	intercept	σ2	log likelihood	aic
-0.1256	-0.3385	0.7121	0.8664	133.5801	0.06726	-1.86	15.72

Once the best ARIMA model has been determined, this model is used for forecasting future values.

In the figure 3 below, the graph of our series including the forecast values according to the model thus constructed

Figure.3 Forecasted values according the ARIMA model



3.1 Training set error measures

Table 3: Training set error measures

ME	RMSE	MAE	MPE	MAPE	MASE
-0.00188616	0.2460309	0.1918204	0.001761065	-0.1435942	0.9609312

4. Exponential smoothing

Exponential smoothing methods are a tool for making forecasts from the past observations of a time series. These methods being relatively basic and simple to implement. In this work we use the simple type of the exponential smoothing method.

Command ets of R gives us the suitable exponential model ets(X , model = "ANN").

4.1 Smoothing parameters:

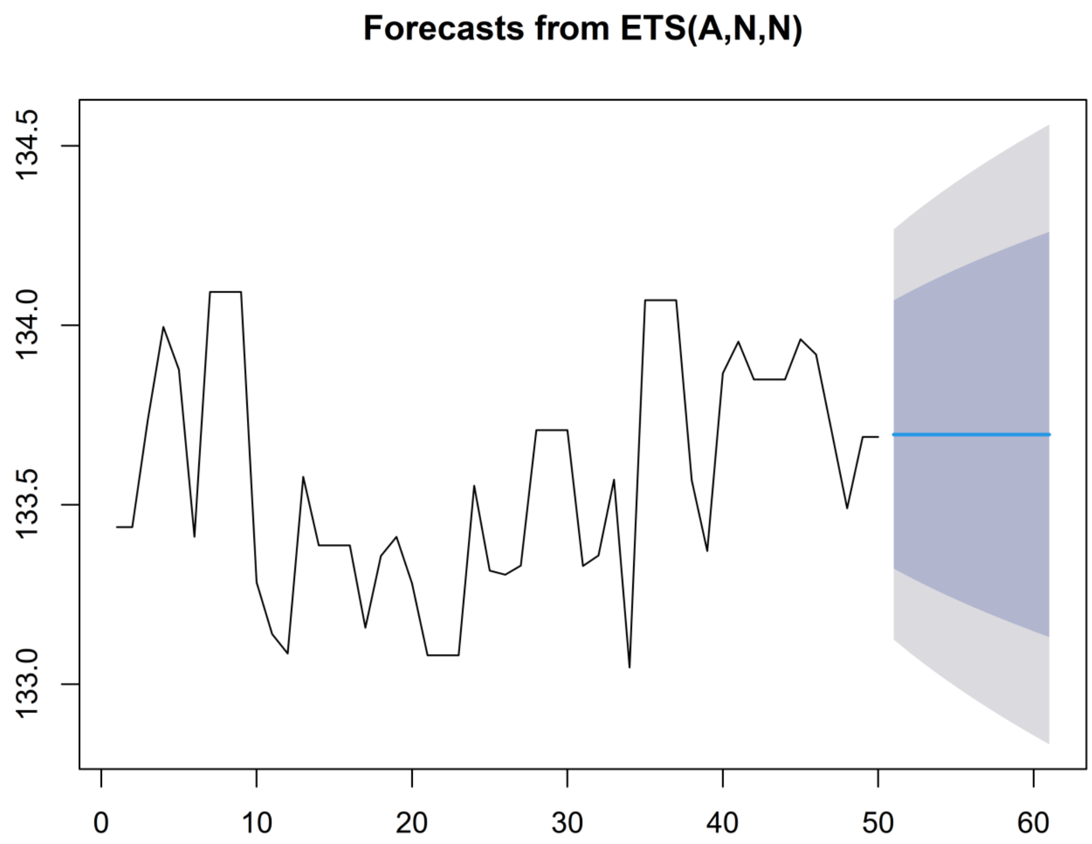
Table 4: Training set error measures

α	l	σ	AIC	AICc	BIC
0.3581	133.5905	0.2914	76.25517	76.77691	81.99124

Once the best exponential smoothing model has been determined, this model is used for forecasting future values.

In the figure 4 below, the graph of our series including the forecast values according to the model thus constructed

Figure.4 Forecasted values according the exponential smoothing model



4.2 Training set error measures:

Table .5. Training set error measures

ME	RMSE	MAE	MPE	MAPE	MASE
0.005877789	0.2855153	0.2218967	0.004023178	0.1660999	1.111599

5.Comparison

We can compare the two models according to the MSE criterion (Mean square error), we see that the MSE of the ARIMA model is smaller than that of the exponential smoothing model.

Table.6. Criteria comparing

Creteria	ME	RMSE	MAE	MPE	MAPE	MASE
Box-Jenkins	-0.00188616	0.2460309	0.1918204	0.001761065	-0.1435942	0.9609312
Expo Smooth	0.005877789	0.2855153	0.2218967	0.004023178	0.1660999	1.111599

5.1 Comparing observed with predicted values for each model

Table.7. Comparing observed and predicted values for each model

Observed values	133.6887	134.1838	134.0557	134.0290	134.0941	134.2760
ARIMA predicted values	133.7344	133.5123	133.5364	133.6085	133.5913	133.5690
ES predicted values	133.6958	133.6958	133.6958	133.6958	133.6958	133.6958

Observed values	134.2760	134.2760	134.2367	134.5325	134.1671
ARIMA predicted values	133.5777	133.5841	133.5804	133.5787	133.5802
ES predicted values	133.6958	133.6958	133.6958	133.6958	133.6958

	MSE
ARIMA predicted values	4.303648
ES predicted values	2.862531

6. Conclusion

The models studied in this article are very powerful and have very good properties. It is clear that autoregressive models are suitable for short-term forecasting although there are other families of models such as NN (neural network) models and genetic algorithm models.

References (APA)

Hyndman, R.J., Khandakar, Y. (2008). Automatic Time Series Forecasting: The forecast Package for R. Journal of Statistical software 27(3), 1-22.

Ljung, G., Box, G. (1978). A measure of lack of _t in time series models. Biometrika 65(2), 297-303.

Granger, C., Newbold, P. (1976). Forecasting transformed series. Journal of the Royal Statistical Society B 38(2), 189-203.

Challis, R.E., Kitney, R.I. (1990). Biomedical signal processing, part 1 time-domain methods. Medical and Biological Engineering and Computing 28(6), 509-524.

Box, G., Jenkins, G.M. (1976). Time series analysis in forecasting and control Applied statistics. Holden-Day, San-Francisco.

Brockwell, P., Davis, R. (1996). Introduction to Time series and Forecasting. Springer, New York.

World Bank, https://data.worldbank.org/country/DZ.

Abderrahmane, B. (2018). Modeling and forecasting in various domains under the theory of autoregression. International Journal of Statistics and Economics, 19(1), 139-146.

Mohamed, B., Abderrahmane, B., Omar, A. (2022). Comparative study between real data and theoretical results calculated by ARIMA model to predict and calculate C02 emissions. Turkish Journal of Computer and Mathematics Education, 13(1), 289-295.