Exchange rate forecasting with Artificial Intelligence

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Abstract
This study concerns the problem of forecasting the exchange rate between the official currency of EU member states, Euro and Albanian Lek, aiming to identify the best predictive model for financial time series future trend prediction. We compare the forecasting performance of linear and nonlinear forecasting models using monthly data for the period between January 2002 until January 2022. We discuss various forecasting approaches, including an Autoregressive Integrated. Moving Average model, a Nonlinear Autoregressive Neural Network model, a BATS model and Exponential Smoothing on the collected data and compare their accuracy using error term measuring indicators, choosing the model with the lowest Mean Absolute Percentage Error value. Finding the most accurate forecasting model would help improve monetary and fiscal politics, as well as orient future personal investments.

Keywords: NARNN, ARIMA, Artificial Intelligence, Time series forecasting.

1. Introduction
The exchange rate affects economic systems in different ways. It impacts economic growth, international trade, interest rates, capital flows, and inflation. In literature, it is defined as the price of a currency versus a foreign currency. Analysing its growth or reduction is crucial when analysing the exchange rate. Countries may choose whether to use a fixed or flexible exchange rate, depending on their monetary politics. Small countries usually go for a fixed exchange rate to attract foreign investments. Thus, it manages to maintain export prices at acceptable levels for foreign buyers and attract foreign investors guaranteeing a stable value of their investments. However, under a fixed exchange rate, a country's monetary policies can become ineffective. It would cause a devaluation of domestic currency, imports would become more expensive and demand for domestic products would increase. On the other hand, flexible exchange rates determine international markets' fluctuations. Developed countries use flexible exchange rate, allowing their currency fluctuate following international market. In this article, we provide forecasts for the Euro/Lek exchange rate using four different time series forecasting models and compare their performance to analyze the advancement of the exchange rate based on the reported data. We aim to forecast future values through a comparison of the performance of these models and provide an analysis of the errors of the forecasts, with the objective to have clear expectation of the future. Finding the most accurate forecasting model would help improve monetary and fiscal politics, as well as orient future personal investments. Using appropriate models and consistently making accurate projections, can help countries to better allocate their resources and prepare for the future.

2. Material and methods
2.1. Material
We considered data published online from Bank of Albania related to Euro/Lek exchange rate for the period from January 2002 to January 2022 considering:

- monthly exchange rate from January 2002 to January 2022 (Figure 1);
- the last 8 months' data as validation set (June 2021- January 2022);

- the last 5 months as test set.

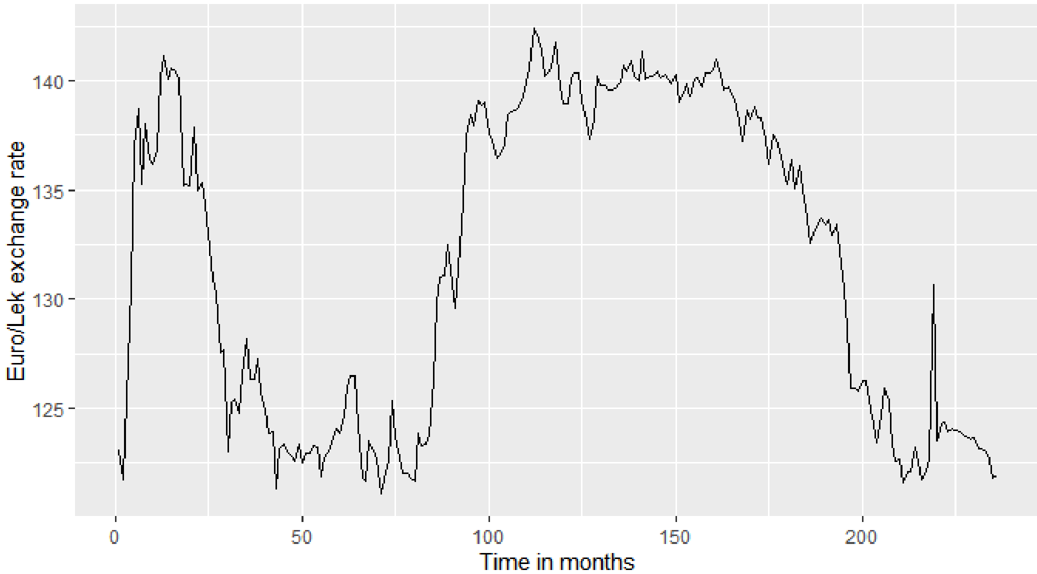

Fig. 1. Euro/Lek exchange rate time series

2.2. Methods

Statistical Analysis: The forecasting was conducted through the R package *forecasting*, which provides methods and tools for forecasting univariate time series. We implemented 3 linear models (Autoregressive Integrated Moving Average - ARIMA, Exponential smoothing state space model with Box-Cox transformation, ARMA errors, Trend and Seasonal component - BATS and Holt's Exponential Smoothing) and a Nonlinear Autoregressive Neural Network - NARNN model and compared their accuracy considering the Mean Average Percentage Error (MAPE) for each of them as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{1}$$

Where:
n – the total number of observations
A_t – the actual value
F_t – the forecasted value.

The principal objective of the ARIMA model is to forecast future values by recognizing the stochastic mechanism of the time series. It represents a time series as a function of its past values, its own lags and the lagged errors, to forecast future values. For the construction of ARIMA model, *auto.arima* function was used. This includes identifying the most suitable lags for the AR and MA components and deciding whether the variable needs differentiation to induce stationary. The model that better fitted our time series data was ARIMA (0,1,0).

The NARN model was developed using the *nnetar* function of "caret" package that fits a neural network model to a time series [1] developed by Hyndman, O'Hara, and Wang. A NARNN (p,k), where p indicates the number of non-seasonal lags used as inputs and k the number of nodes in the hidden layer, can be described as an AR process with nonlinear functions.We chose a (1-6-1) network, with 1 lag as input node and 6 hidden layer nodes and 19 weights. It has the form of a feedforward three-layer ANN, where neurons have a one-way connection with the neurons of the next layers [2].

3. Results

RMSE, MAE, MPE, MAPE, ME and MASE accuracy indicators were used to measure the performance of the models and their accuracy. In addition to the graph, the above values (Table 1) show that the NARNN model gives more accurate forecasting values than the ARIMA model and the other linear forecasting models considering the validation data. In comparison to ARIMA, NARNN model has improved the forecasting accuracy by 24% according to ME and by 1% according to RMSE. The NARNN model gives better results in almost all the considered indicators with a considerable difference from the indicators of the other models. It has improved the forecasting performance, according to the ME indicator, by 67% compared to Holt's model and by 35,7% compared to BATS. According to the MAPE indicator, the NARNN model has improved by 2% compared to ARIMA, 3,2% compared to Holt's model and 3,7% compared to BATS.

We considered as the most accurate forecasting model the one with the lowest MAPE value, as it is recommended as an accuracy comparing unit when using different methods on a time series, considering as the most accurate model the one with the lowest MAPE value. NARNN model has the minimal MAPE for the training set (0,7232%).

Table 1. Accuracy of training data

Accuracy indicator	Model			
	NARNN	ARIMA	Holt's	BATS
ME	-0,1087	-0,0043	0,0016	0,0801
RMSE	1,5064	1,4917	1,5228	1,1207
MAE	0,9708	0,9575	0,9771	0,9813
MPE	-0,0820	-0,0101	-0,0065	-0,0054
MAPE	0,7232	0,7313	0,7472	0,7511
MASE	1,0101	0,0094	1,0167	1,0204

Source: Author own work

In Table 2 we present the MAPE value for the last 8 months (validation set), while Table 3 presents forecasts for each model for the validation set. We can observe that again NARNN model gives the most accurate forecasts for the validation set, as the difference between actual data and forecasted data is lower compared to other model. This fact confirms once again our assumption about choosing the most accurate model for our time series.

Table 2. MAPE (%) for last 8 months validation set

Accuracy indicator	Model			
	NARNN	ARIMA	Holt's	BATS
MAPE	0,386	0,629	0,533	1,611

Source: Author own work

Table 3. Forecasts for validation set

Date	Model				
	Actual data	NARNN	ARIMA	Holt's	BATS
June 2021	121,54	121,92	121,95	121,96	122,65
July 2021	122,84	121,89	121,95	121,97	122,99
August 2021	121,19	121,84	121,95	121,98	123,21
September 2021	120,76	121,83	121,95	121,99	123,35
October 2021	120,90	121,80	121,95	122,00	123,46
November 2021	121,32	121,77	121,95	122,00	123,54
December 2021	121,62	121,75	121,95	122,01	123,60
January 2022	121,10	121,72	121,95	122,02	123,65

Source: Author own work

Figure 2 presents a graphic representation of forecasts for each model. We can observe that ARIMA model shows a steady trend for the next 5 months, with values between 132,5 and 112,5. As can be seen from the graph, the predicted values follow the trend and the seasonality of our time series validation data. The confidence interval indicates that accurate forecasts can vary within that interval (marked in blue in Figure 2a).

If we compare the values of eight months used as a test set, we notice that there are differences between the values predicted by ARIMA model and the values observed from the collected data. This is emphasized by the value of MAPE for the eight months test, which for the ARIMA model reaches 0,629%. For the construction of the NARNN model (Figure 2d), the data were divided into two sets; training set and testing set. The training set was used to create the model, while the test set was used for the evaluation of the created model [3]. The network structure was chosen based on the results of Zhang et al. [4], who showed, through simulation, that the best network structure corresponds to one hidden layer with a maximum of two neurons. Since the network with 6 hidden neurons performed better than the ones with 1, 2, 3, 4 and 5 hidden neurons in terms of difference between actual and forecast data, we chose 6 hidden components for our model because it had a low RMSE in comparison to other models. The input layer neurons were chosen by the function *nnetar* and accuracy. They gave as output a neural network with 1 input neuron. Figure 2b presents the forecasting results of NARNN model for the following 5 months for Euro/Lek exchange rate.

The NARNN model values follow very well the time series' trend, thanks to the training and learning process, which enable the model to better understand the time series' features. All components are well-presented and the difference between the predicted values and the time series observed values tends to zero, as the nonlinear component of the time series is taken in consideration by the nonlinear model. This is also emphasized by the value of MAPE for the test set, equal to 0,386%, lower than other forecasting models' MAPE values. According to the NARNN (1-6-1) model, there will be an increase in the Euro/Lek exchange rate by the end of June.

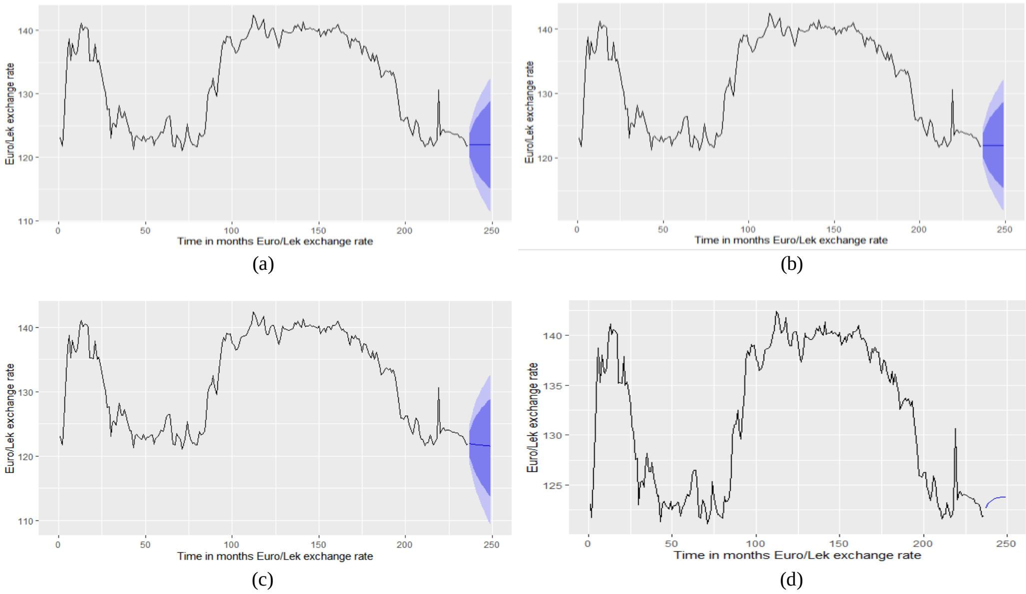

Fig 2. Forecasts from models: (a) ARIMA; (b) BATS; (c) Holt's; (d) NARNN model.

Figure 2c ad 2b show predictions obtained through Holt's and TBATS model [5]. BATS model had a poor accuracy compared to the previous two models, as it had higher MAPE, RMSE, ME and MAE in comparison to the other two models. They show a relatively steady linear trend for the future 5 months values, with a light increasing tendency for the Holt's linear model, accompanied by relatively wide confidence intervals, that correspond to a higher degree of uncertainty for the forecasts.

Table 4: Forecasts for 6 months ahead

Date	Model			
	NARNN	ARIMA	Holt's	BATS
February 2022	121,69	121,95	122,01	123,69
March 2022	121,66	121,95	122,01	123,73
April 2022	121,63	121,95	122,02	123,75
May 2022	121,60	121,95	122,02	123,77
June 2022	121,57	121,95	122,02	123,79

Source: Author own work

Table 4 presents results for 6 months ahead forecasting for the considered forecasting models.

4. Discussion and conclusion

In this paper, we have evaluated four different time series forecasting models for predicting monthly Euro/Lek exchange rate for the next 5 months. Our findings evidenced the differences between each model accuracy when forecasting and their performance. Using multiple models let us test and compare their forecasting accuracy and make an optimal selection. For our time series, NARNN model was preferred over the other linear forecasting models. It was chosen based on MAPE value, as it had the lowest value among all the forecasting models. In addition, in comparison to ARIMA, NARNN model has improved the forecasting accuracy by 24% according to ME and by 1% according to RMSE. The NARNN model gives better results in almost all the considered indicators with a considerable difference from the indicators of the other models. It has improved the forecasting performance, according to the ME indicator, by 67% compared to Holt's model and by 35,7% compared to BATS. According to the MAPE indicator, the NARNN model has improved by 2% compared to ARIMA, 3,2% compared to Holt's model and 3,7% compared to BATS.

NARNN model had the minimal MAPE for the considered period (0,386%). The NARNN (1-6-1) model predicted an increase in the Euro/Lek exchange rate for the next 5 months. The results are valid for a short period of time because in the long run they can be influenced by other factors such as inflation, monetary policies, economic crisis, etc.

Similarly, the above considered models can be implemented on new data as they become available, for possible future exchange rate forecasting, in order to improve forecasting accuracy. It would also be interesting to consider other currencies' exchange rate or make a daily based analysis.

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Conflict of Interest

The authors have declared that there is no conflict of interest.