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Forecasting the Fluctuation of Currency Exchange Rate Using Random Forest

L. Basha, E. Gjika

***Abstract*—**The exchange rate is one of the most important economic variables, especially for a small, open economy such as Albania. Its effect is noticeable on one country's competitiveness, trade and current account, inflation, wages, domestic economic activity and bank stability. This study investigates the fluctuation of Albania's exchange rates using monthly average foreign currency, Euro (Eur) to Albanian Lek (ALL) exchange rate with a time span from January 2008 to June 2021 and the macroeconomic factors that have a significant effect on the exchange rate. Initially, the Random Forest Regression algorithm is constructed to understand the impact of economic variables in the behavior of monthly average foreign currencies exchange rates. Then the forecast of macro-economic indicators for 12 months was performed using time series models. The predicted values received are placed in the random forest model in order to obtain the average monthly forecast of Euro to Albanian Lek (ALL) exchange rate for the period July 2021 to June 2022.

***Keywords*—**Exchange rate, Random Forest, time series, Machine Learning, forecasting.

I. Introduction

EXCHANGE rates play a very important and critical role for most of the world's free market economies. This is one of the reasons why exchange rates are among the most analyzed and governmentally manipulated economic measures. Exchange rate forecasting and strategy have become the main research part of institutions in different countries. The economic effects of the exchange rate changes are among the most controversial issues in the literature. Particularly, the effect of exchange rate changes on economic growth has become one of the most important research topics over the past decades. The arguments that are put forward by classical and structuralist economists related to the link between exchange rate and economic growth, using data belonging to Turkey's economy are tested by [1]. In [2], a five-year sample from 1970 to 2010 determined exogenous real exchange rate movements, especially those not triggered by country-particular increase shocks, in a sample of 150 countries. They find that real depreciation (appreciation) has a considerable and statistically significant positive (negative) impact on real per capita growth across five-year average periods. The relationship between exchange rate and economic growth for 54 developing countries over the period 1990–2010 is examined in [3]. The empirical result showed that the indirect impact of currency undervaluation on growth in developing countries is negative and statistically significant. For frequency less than annual, such as daily, weekly, or even monthly, exchange rates are thought to follow a random walk process, according to prevailing opinion in the field of exchange rate economics. At lower frequency, exchange rates do, however, exhibit some trending, cyclicality, or overall historical reliance. The relationship between exchange rates and current order flow as well as the predictability of lagged order flow on the future exchange rate is reviewed in [4]. One of the top interdealer electronic broking systems is used and they employ intraday high-frequency transaction data.

To forecast the exchange rate, financial models by analyzing the macroeconomic parameters of time series are increasingly used by government agencies and institutions. Fluctuations of exchange rate have a direct regulating effect on import and export trade between countries. Exchange rate is subject to changes in interest rates, inflation, national politics, and the economy of each country. A well founded and precise model, which uses a hybrid path of the combination of quantile regression forest and Gaussian kernel smoothing method, is investigated in [5]. Reference [5] shows that the proposed model works very well due to the use of exchange rate data between the US Dollar (USD) and the Kenyan Shilling (AH). Different economic factors such as: interest rate, money supply, foreign direct investment, real gross domestic product, and consumer price index are also used to evaluate exchange rate performance. The link between nominal exchange rate volatility and aggregate domestic consumption using data from 12 emerging economies is studied in [6]. The outcome of the report shows that while exchange rate uncertainty has short-run effects on domestic consumption of almost all countries, the short-run effects last into the long run only in half of the countries. Analysis of the relationship between exchange rate risk exposures, which are calculated as the sensitivity of stock price changes to exchange rate movement, and the Japanese enterprises' exchange rate risk management based on the 2009 RIETI survey is provided in [7]. Empirical results confirm that large Japanese manufacturing industries have a significant exposure to exchange rate risk; firms with greater dependence on foreign sales have a larger foreign exchange exposure and the higher the US dollar invoicing ratio, the greater the foreign exchange exposure, but risk is reduced by financial and operational hedging. The two main indices of an economy's overall performance are inflation and currency rates. In [8], a copula approach is suggested for assessing the correlation between inflation and exchange rate. It was followed by the fitting of marginal distributions from the residuals using GARCH(1,1) before the authors got the uniform margins from these

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univariate distributions for copula estimation. According to the findings, there is a 7% or so correlation between inflation and currency rate. Reference [9] surveys the central process of exchange data analysis, computation, and portfolio selection during dealing and funding in exchange derivatives. From the whole process of exchange trading and investment, they build a two-objective optimization model for prediction of exchange rate data. Exchange rate forecasting is required for local speculation, direct foreign investment, strategic planning, and exhibition to safeguards transactions, accounting and protection of economic openness, short-term and long-term financing and establishing a foreign balance of payments. The powers of the economy set the exchange rates. Analyzing and forecasting exchange rates time series is a challenging task for the scientific community due to its nonlinear, complex and irregular structural feature. Reference [10] forecasted the exchange rate by a combination of ARIMA and ANN models. The results concluded that combined models performed better forecasting than individual prediction models. Combining typical exchange rate models with machine learning and Taylor Rule models performs better forecasting than individual models [11]. In [12], a synthesis of conventional economic models and analyses with contemporary machine learning approaches is offered. To outperform the forecast performance, the random forest and neural network models are merged. With the random walk, the findings demonstrate substantially higher predictive accuracy, although some results with the random forest demonstrate accuracy comparable to the random walk. Reference [13] investigates how real effective exchange rate fluctuation impacts Central and Eastern European (CEE) economic growth.

The exchange rate is a totally essential monetary variable, especially for a small, open economic system such as Albania. Its importance is due to the impact that this indicator has on the country's competitiveness, commerce, bank balance, consumer price index, salary and home economics. Predicting exchange rates is actually a difficult task, a really vital analysis space for monetary establishments. It is a very important area of research not only for financial institutions and economists, but for all experts in the forex market, to create a stable economic environment.

Fluctuations in the exchange rate can affect aggregate demand and investment expansion, while an overvalued currency negatively affects employment. A persistently over valuated real exchange rate is an early indicator of potential currency crisis. There are done many studies which investigate the correlation and ability of many economic indices in some important indicators of the Albanian economy [14]-[16]. There are some models that use time series methods for forecasting indicators, for monthly or quarterly frequencies. This paper is one of the first to address machine learning models to understand the dependence of these indicators and to obtain forecasts in the future. In this regard, in this work we explore the monthly average euro to ALL exchange rate. The period of time studied is from January 2008 to June 2021. Furthermore, the study examines whether macroeconomic factors have a significant effect on the exchange rate fluctuation of Albania such as: consumer price index; the monetary aggregates, AM3 - broad money; gross external debt position; monetary base; currency outside depository corporations; real gross domestic product with market prices and current accounts, using machine learning techniques and time series models. RStudio statistical software is used as the environment of all analysis.

The paper is structured as follows: Section II presents the theoretical concepts of the paper. An overview of random forest algorithm, time series model and metrics used to evaluate the performance of the point and interval predictions is presented in this section. In Section III, a case study using monthly average foreign currency Euro to ALL exchange rate and selected macro-economic variables are presented. Also, data analysis, graphical presentations, tables and results are presented here. The conclusion is presented in Section IV.

II. Methodology

A. Exponential Smoothing

Time Series Analysis is the most widely used area of data science. Time series forecasting uses historical data from the past to make predictions about the value of a variable in future occurrences while characterizing trends, seasonality, and noise. A number of time series forecasting techniques, including moving average, exponential smoothing, ARIMA, recurrent neural networks, gradient boosting, fuzzy time series algorithms, etc., are accessible depending on the problems and the data collection. Seasonality and trends are typically present in real-world data. One of the earliest time series analysis methods, Holt-Exponential Winter's Smoothing considers level, trend, and seasonality [17], [18].

Simple Exponential Smoothing, which was first presented in the late 1950s [17]-[19] and served as the inspiration for some of the most effective forecasting techniques, assumes that the time series has not changed in level. Predicted values are calculated using the weighted average. As time goes on, from the past to the present, weights increase exponentially, with recent observations having the greatest weight. The predicted value is calculated as:

$$\hat{y}_{t+1|t} = \alpha y_t + \alpha(1-\alpha)\hat{y}_{t|t-1} \tag{1}$$

where $0 \le \alpha \le 1$ is the smoothing parameter, y stands for the original observation, $\hat{y}_{T|T-1}$ is the previous predicted value.

Holt's Exponential Smoothing: Holt is an extension of the simple exponential smoothing method, to analyze time series, where data represent a trend. The method consists of a formula that considers the level and a formula that takes into account the trend. It also contains the equation for predicting values:

$$\begin{aligned} &\textit{Forecast equation} && \hat{y}_{t+h|t} = l_t + hb_t \\ &\textit{Level equation} && l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1}) \\ &\textit{Trend equation} && b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \end{aligned} \tag{2}$$

where l_t represents an estimate of the series' level at time t, b_t indicates an estimate of the series' trend at time t. The smoothing parameters for levels and trends are α and β, respectively.

Holt-Winters' Exponential Smoothing: The forecast equation and three smoothing equations for the level l_t, trend b_t, and seasonal component s_t, make up the Holt-Winters seasonal approach. The appropriate smoothing parameters are α, β, γ, with *m* standing for the frequency of seasonality. Depending on the seasonal component, this method is divided into two parts. If the variations are constant across the series, the additive method is used, otherwise, when the variations change in proportion to time, the multiplicative method is used.

The additive method is:

$$\begin{aligned} \hat{y}_{t+h|t} &= l_t + hb_t + s_{t+h-m(k+1)} \\ l_t &= \alpha(y_t - s_{t-m}) + (1-\alpha)(l_{t-1} + b_{t-1}) \\ b_t &= \beta(l_t + l_{t-1}) + (1-\beta)b_{t-1} \\ s_t &= \gamma(y_t - l_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m} \end{aligned} \tag{3}$$

The multiplicative method is:

$$\begin{aligned} \hat{y}_{t+h|t} &= (l_t + hb_t)s_{t+h-m(k+1)} \\ l_t &= \alpha\frac{y_t}{s_{t-m}} + (1-\alpha)(l_{t-1} + b_{t-1}) \\ b_t &= \beta(l_t + l_{t-1}) + (1-\beta)b_{t-1} \\ s_t &= \gamma\frac{y_t}{l_{t-1} + b_{t-1}} + (1-\gamma)s_{t-m} \end{aligned} \tag{4}$$

B. AutoRegressive Integrated Moving Average

AutoRegressive Integrated Moving Average (ARIMA) model provides another approach to time series forecasting. The main purpose of ARIMA models is to describe the autocorrelations in the data, in contrast to the exponential smoothing methods which study the level, trend and seasonality of the time series data. The model is:

$$y_t^{'} = c + \phi_1 y_{t-1}^{'} + \ldots + \phi_p y_{t-p}^{'} + \theta_1\varepsilon_{t-1} + \ldots + \theta_q\varepsilon_{t-q} + \varepsilon_t \tag{5}$$

where $y_t^{'}$ is the differenced series, *p* is the order of the autoregressive part, *d* is the degree of first differencing involved, *q* is the order of the moving average part.

As is clear from (5), this model is taken as a combination of differentiation with autoregression and a moving average model. The "predictors" on the right-hand side include both lagged values of y_t and lagged errors.

To get the points predicted, the model is initially expanded so that y_t is on the left-hand side and all other terms are on the right. Then *t* is replaced by *T+h*. In the end future observations are replaced with their forecasts, future errors with zero, and past errors are replaced with the corresponding residuals. These steps are then repeated until all predicted values have been calculated [20].

C. Random Forest

Random forest is a well-known supervised machine learning technique that solves regression and classification issues [21]. It is a substantial modification of bagging that builds a large collection of de-correlated trees, and then averages them. It is a method that makes use of ensemble learning and combines numerous weak classifiers to offer answers to challenging issues. Enhancing the decrease in bagging variance by reducing inter-tree correlation, without increasing variation, is the concept of random forests.

Random selection of input variables enables the achievement of this objective in the tree growth process. After *B* such trees $\{T(x;\Theta_b)\}_1^B$ are grown, the random forest (regression) predictor is:

$$\hat{f}_{rf}^{B}(x) = \frac{1}{B}\sum_{b=1}^{B} T(x;\Theta_b) \tag{6}$$

where Θ_b characterizes the *bth* random forest tree in terms of split variables, cutpoints at each node, and terminal-node values.

Random forest algorithm uses out-of-bag (oob) samples to measure the predictive power of each factor. The oob samples are sent down the tree as the bth tree grows and the accuracy of the prediction is also reported. The accuracy is once more computed, after the random permutation of the jth variable within the oob samples. The number of samples that reach the node divided by the entire number of samples gives the node probability. For each decision tree, the importance of the nodes including only two child nodes is calculated:

$$mi_j = w_j D_j - w_{left(j)} D_{left(j)} - w_{right(j)} D_{right(j)} \tag{7}$$

where *mi* is the importance of node j; *w* is the weighted number of samples reaching node j; *D* is node j's impurity value; *left(j)* is the left child node split on node j; *right(j)* is the right child node split on node j. On a decision tree, the significance of each variable is calculated as:

$$v\, i_i = \frac{\sum_{j:node\ j\ splits\ on\ feature\ i} mi_j}{\sum_{r \in all\ nodes} mi_r} \tag{8}$$

where *vi var(i)* = the importance of variable i. By dividing this value by the sum of all variables importance values we can take values between 0 and 1:

$$norm\ vi_i = \frac{vi_i}{\sum_{j \in all\ features} vi_j} \tag{9}$$

The average of the feature's importance value over all the trees, gives the final feature importance and is:

$$RFvi_i = \frac{\sum_{j \in all\ trees} normvi_{ij}}{B} \quad (10)$$

where *RFvi var(i)* is computed the *i* feature's relevance using data from all the trees in the Random Forest model. In a tree j, *normvi* is the normalized feature significance for i; *B* = total number of trees.

D. Evaluation Metrics

Model accuracy is important when dealing especially with prediction. The evaluation of many prediction models from classical to advanced methods is mainly based on the below error measurements: mean absolute percentage error, mean square error, root mean square error and R-squared. In this study we have considered these standard errors to evaluate the effectiveness and accuracy of the algorithms. Formulas for these measurements are as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - p_i}{y_i}\right| \times 100\% \quad (11)$$

$$MSE = \sum_{i=1}^{n}\frac{(y_i - p_i)^2}{n} \quad (12)$$

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(y_i - p_i)^2}{n}} \quad (13)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - p_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (14)$$

where y_i and p_i are the i_{th} actual and predicted values.

III. Case Study

A. Data Selection and Description

Our empirical analysis investigates the fluctuation of Albania's exchange rates using a monthly average foreign currency Euro to ALL exchange rate with a duration from January 2008 to June 2021, Fig. 1.

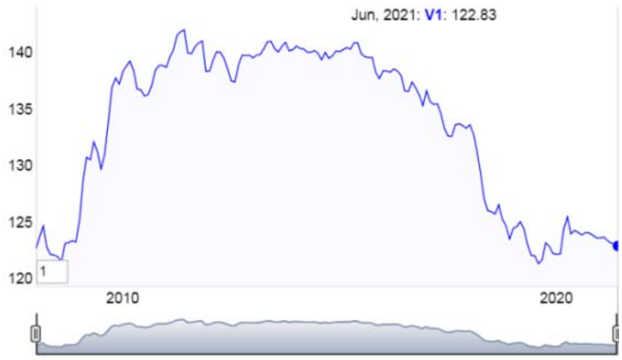

Fig. 1 Monthly average foreign currency Euro to ALL exchange rate

Box plot of the annual exchange rate is visually presented in Fig. 2. In 2016, 2017, 2018 and 2019 there is a large fluctuation in the foreign exchange rate Euro/Lek. While in 2020 and 2021 there is a more stable exchange rate situation. During 2020 we observe some outliers which may be effect of the COVID-19 pandemic. And the same distribution and approximate levels are observed during the period considered for 2021. Here we want to emphasize also the role of COVID-19 in many economic indices. Furthermore, we have examined whether macroeconomic factors have a significant effect on the exchange rate fluctuation of Albania such as: consumer price index (CPI); the monetary aggregates, broad money (AM3); gross external debt position (GED); monetary base (MB); currency outside depository corporations (CODC); real gross domestic product (GDP) with market prices and balance of payment: current accounts (BP).

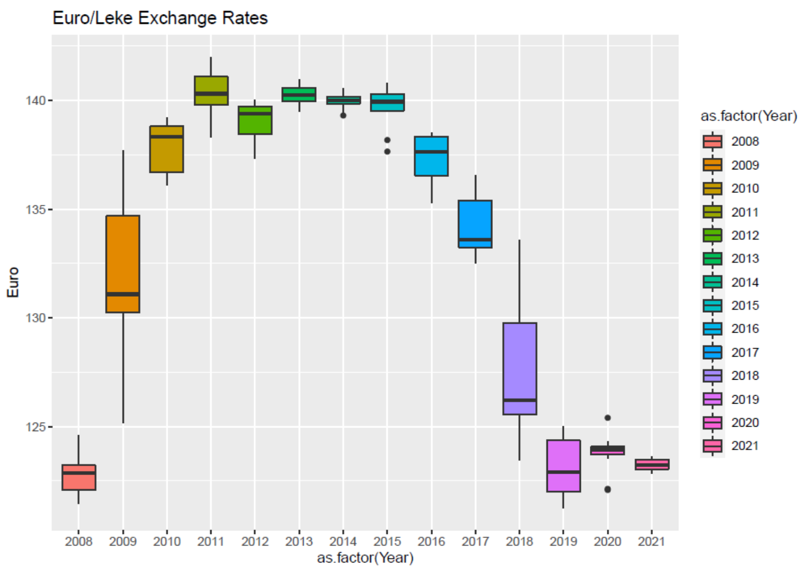

Fig. 2 Box plot of the annual exchange rate

CPI is defined as the measure of the average change of prices of a fixed basket of goods and services, which is purchased by households, and which aims to satisfy the households' needs. This index is the official index to measure inflation in Albania [19]. The Institute of Statistics in Albania provides CPI in Albania with base December 2020=100. In Albania, there are three monetary aggregates. M1 is defined as the sum of money held outside of depository institutions, transferable deposits, and non-term deposits in resident sectors (excluding banks and central government). Term deposits in resident sectors are added to M1 to create M2 (excluding banks and central government). Broad money (M3) is made up of M2 plus the foreign currency deposits of resident sectors (excluding banks and government).

Albanian external debt states, as gross debt, only one sub-category of the liabilities of Albania reported in the international investment position vis-à-vis other countries.

Only financial instruments with debt character are included in external debt. The most commonly used measure of the size and the performance of an economy is GDP. The GDP is the total value of all of goods and services that have been produced minus the value of the goods and services needed to produce them. The current account balance gives a measure of a country's level of international competitiveness.

CPI and real GDP with market prices were sourced from the Institute of Statistics [22]. The monetary aggregates, broad money; GED; MB; CODC and balance of payment: current accounts were sourced from the Bank of Albania [23].

For each of the macroeconomic factors, monthly data were obtained for a period of 163 months from January 2008 to June 2021. Summary statistics for the sampled monthly period from 2008 to 2021 are given in Table I.

TABLE I
SUMMARY STATISTICS OF THE VARIABLES

Variables	Min	Max	Mean	Std	skewness	Kurtosis
Euro	121.3	142.0	133.3	7.113903	-0.4926716	-1.465722
MB	213578	534347	342289	77050.12	0.6231037	-0.3202316
CODC	144960	354987	226976	49174.91	0.8084708	0.04547035
AM3	754514	1501614	1130341	185552.5	-0.4107545	-0.5968113
CPI	273.8	366.7	321.9	25.16713	-0.204152	-1.034851
GED	295000	1121578	841689	250779.2	-0.708513	-0.9771005
BP	-453.3	-115.7	-261.0	75.00207	-0.1586933	-0.6100384
GDP	237901	482514	354289	52981.66	0.05776862	-0.5166028

B. Experimental Results and Discussion

In our work for the analysis of the fluctuation of monthly average foreign currency Euro to ALL exchange rate analysis and the macroeconomic factors taken in the study, we have divided it into two main parts.

First the Random Forest Regression algorithm is constructed to find the impact that economic variables have in the behavior of monthly average foreign currencies exchange rates. To build the random forest model, the training part of the data from January 2008-June 2019 was used and then for testing the model, the data in the period July 2019-June 2021 were used. Fig. 3 gives the realization flowchart of the random forest model.

Second the forecast of macro-economic indicators which have a significant effect in currency exchange rate is obtained for 12 months using time series models. The forecasting models of the series that affect the exchange rate are built based on testing and training. The training part of the data is from January 2008-June 2019 and the testing part includes the data from July 2019-June 2021. The predicted values received are placed in the random forest built model, in order to make the average monthly forecast of the Euro to ALL exchange rate, for July 2021 to June 2022, Fig. 4.

We have adjusted parameters in order to ameliorate the forecasting power of the model. The parameters are: the number of decision trees; the number of variables examined by each tree when splitting a node.

We created a customized Random Forest model to fine-tune the parameters, comparing the results for several parameter combinations with the optimal set for our model.

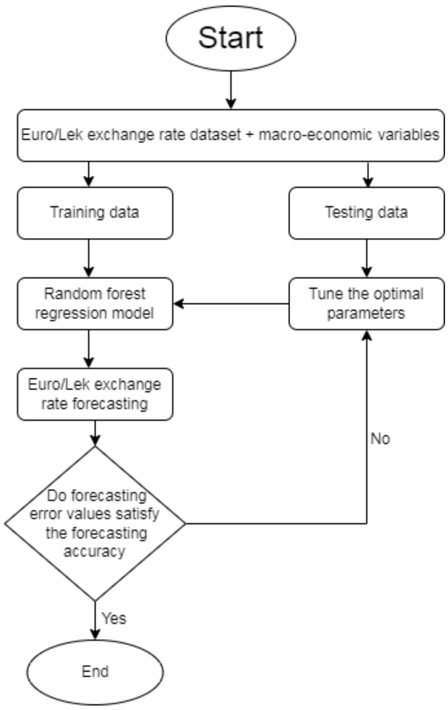

Fig. 3 The flow diagram of random forest model

According to Fig. 5 the best parameters for our model are 900 trees and 90 maximum nodes. For this algorithm, we used all available variables, but some of them contain more predictive power than others.

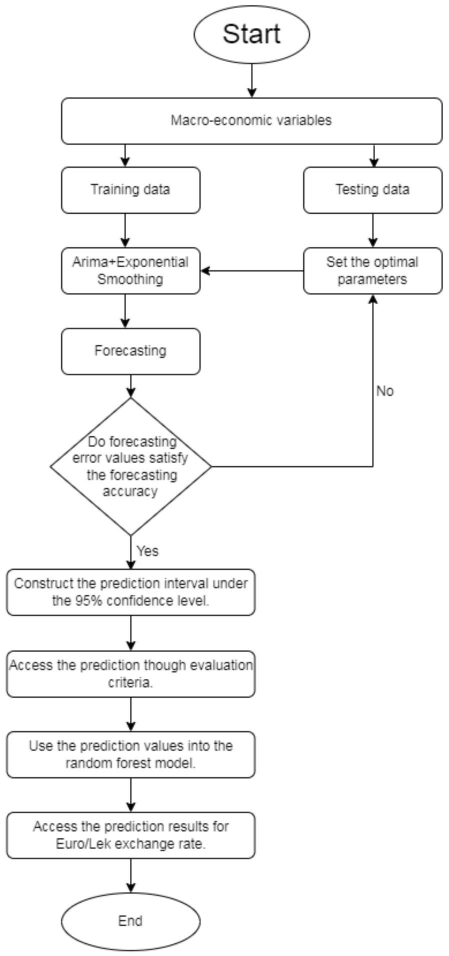

Fig.4 The flow diagram of final model

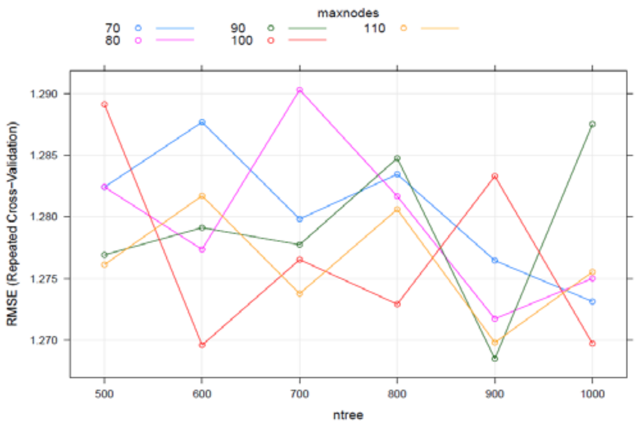

Fig. 5 Tune of the parameters

The significance of the variable is calculated as the reduction in the impurity of the node, weighted by the likelihood of achieving this node. For each division in each tree, improving the division criterion is the measure of the importance assigned to the division variable and accumulates. The higher the value of increase node purity, the more significant the feature.

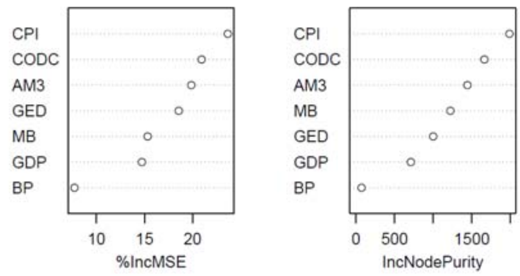

Fig. 6 Variable importance plots

The plot of Fig. 6 and Table II show the importance of variables. We can clearly see that CPI and CODC have significant importance in the behavior of the exchange rate.

The x-axis in Fig. 7 runs from 0 trees to the most trees that might be split by any variable, which in this case is 900 and is achieved by all variables depicted.

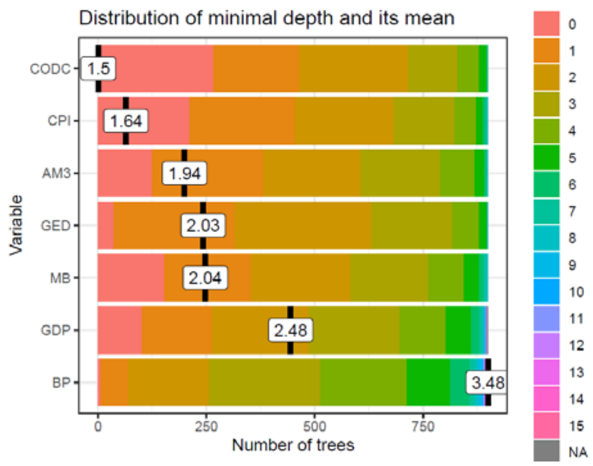

Fig. 7 Distribution of minimal depth

We have explored the relations between different importance measures, given in Table II. After this step, the three indicators that are least in agreement with each other are selected. These indicators are used in the next step to construct the graph of the importance of the variables, to select the most influential factors, Fig. 8.

We can observe that while all of the indicators shown are strongly connected, some are more so than others. When comparing the rankings two measures almost exactly agree in their rankings of variables: mse increase vs. node purity increase. With these pairs, we have built the multi-way importance plot: Fig. 9. The superiority of CODC and CPI is clear in all three dimensions plotted.

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TABLE II
VARIABLE IMPORTANCE

Variables	mean_min_depth	no_of_nodes	mse_increase	node_purity_increase	no_of_trees	times_a_root	p_value
MB	2.02600	3749	9.2851	1222.2326	500	73	3.6725e-02
CODC	1.61600	4101	20.987	1663.1678	500	133	8.6409e-16
AM3	1.92800	4167	14.443	1443.0178	500	80	4.5317e-20
CPI	1.50200	4007	19.625	1987.7553	500	130	1.2518e-10
GED	1.98800	4487	10.688	999.7813	500	25	2.5414e-48
BP	3.40228	2421	0.6328	71.7931	498	3	1.0000e+00
GDP	2.44428	2605	5.8592	710.5493	498	56	1.0000e+00

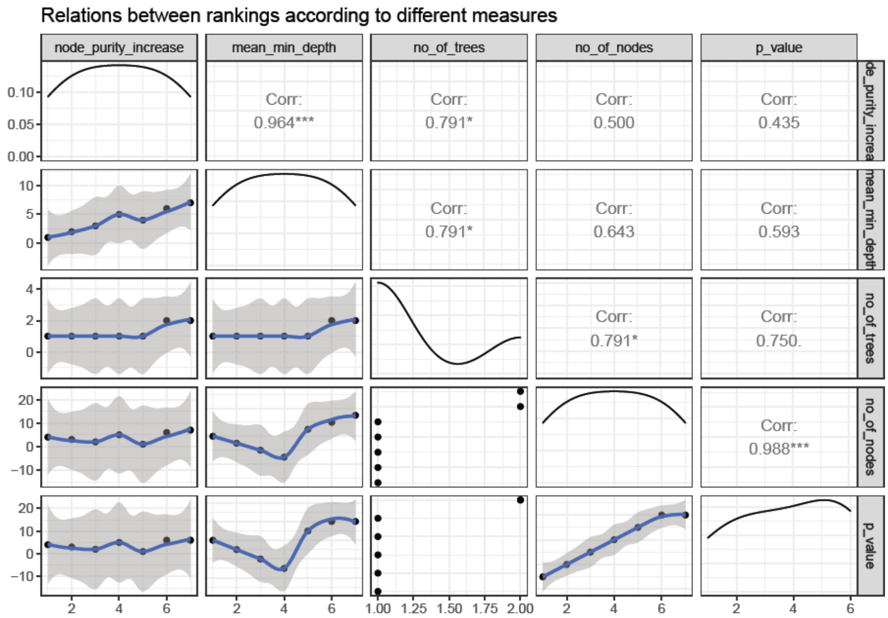

Fig. 8 Relation between measures

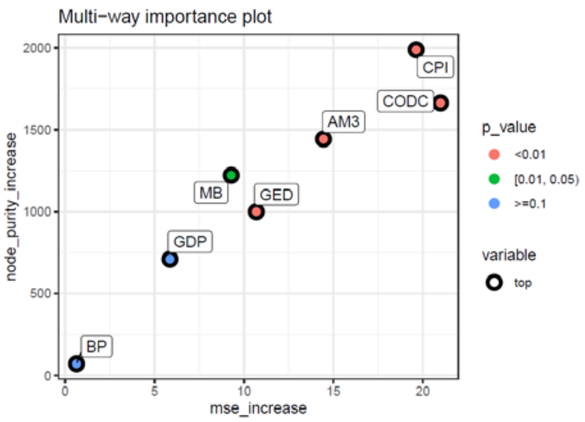

Fig. 9 Multi-way importance plot

In Fig. 9, we see that GDP and BP are not significant according to our *p-value*, which is a derivative of the number of nodes that use a variable for splitting.

As a result of our pre-trained model, we can now forecast the values of the test data. The accuracy of the model is then evaluated by comparing the predicted values with the actual values in the test data, where: Mean of squared residuals is 1.462; % Var explained is 97.09; MSE is 0.287; R-squared is 0.9945; (OOB) R-squared is 0.956 and (OOB) Error rate is 2.181.

The second part of our analysis consists in the analysis of each macroeconomic indicator, through time series methods. The following functions are available for each variable: plots the data along a curve to examine the relationships between the variables within the data; recognizes patterns in time series data, such as trends, cycles, or seasonal variation. The time series data are subjected to an exploratory analysis by being highlighted for the key traits. After selecting the best model for each explanatory variable, the respective models are used to obtain the predicted values of the indicators for 12 months. Time series forecasting techniques which are used are: Exponential Smoothing and ARIMA models. Fig. 10 presents the time series of indicators together with the predicted values.

The predicted values received for each of the variables are placed in the random forest built model, in order to obtain the average monthly forecast of the Euro to ALL exchange rate, for July 2021 to June 2022. Results are given in Table III and plotted in Fig. 11.

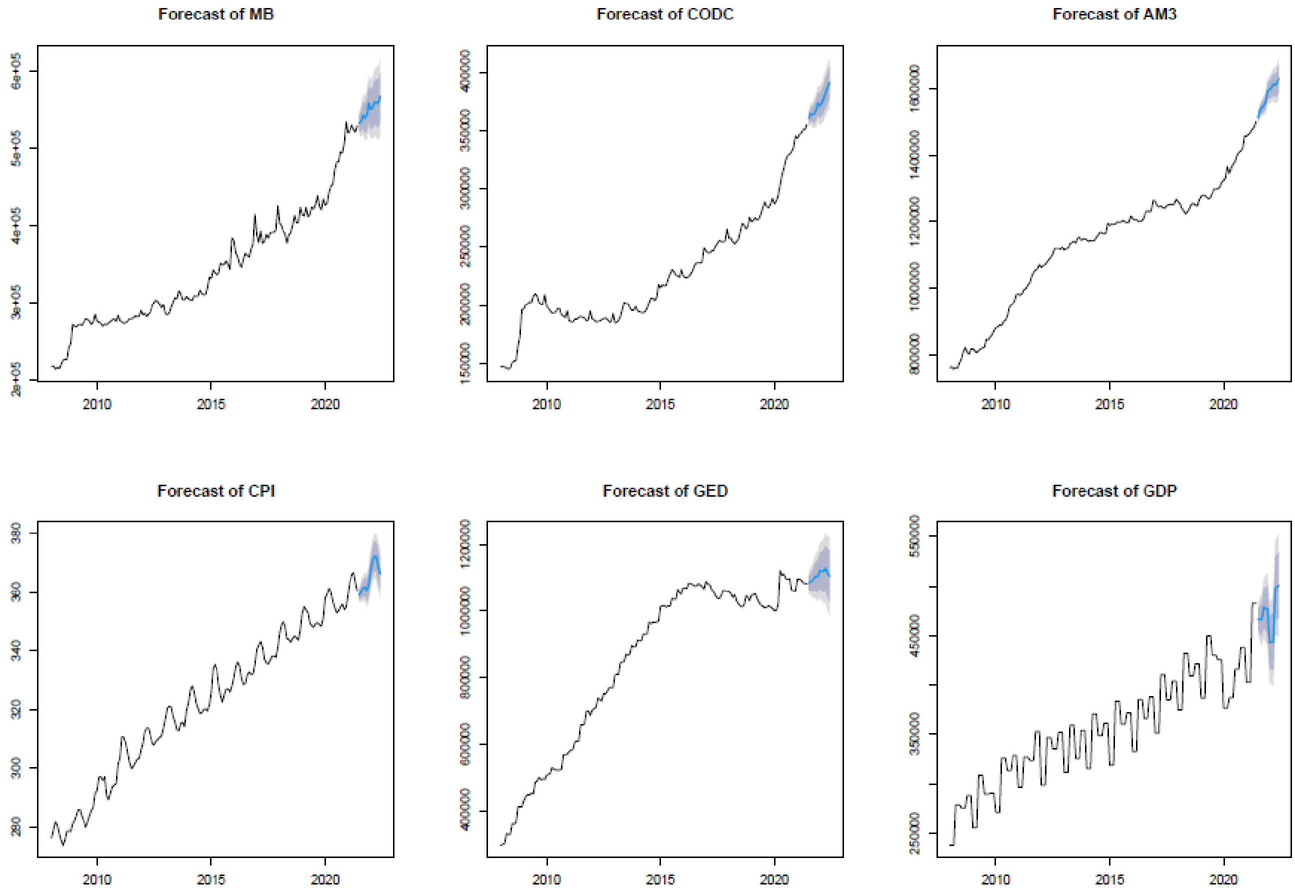

Fig. 10 Forecast of the indicators

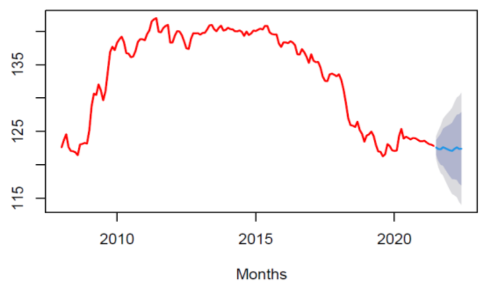

Fig. 11 Forecast of Euro/Lek exchange rate

TABLE III.
PREDICTED VALUES

Months	Forecast	Lo 95	Hi 95
Jul 2021	122.6193	121.0026	124.2360
Aug 2021	122.3737	119.6534	125.0939
Sep 2021	122.3241	118.7965	125.8517
Oct 2021	122.6456	118.4322	126.8590
Nov 2021	122.4949	117.6644	127.3254
Dec 2021	122.3229	116.9199	127.7259
Jan 2022	122.1635	116.2189	128.1080
Feb 2022	122.0906	115.6274	128.5539
Mar 2022	122.4032	115.4384	129.3680
Apr 2022	122.6242	115.1711	130.0774
May 2022	122.3878	114.4567	130.3189
Jun 2022	122.4177	114.0168	130.8186

IV. CONCLUSION

Our empirical analysis explores the fluctuation of Albania's exchange rates using a monthly average foreign currency Euro to ALL exchange rate with duration from January 2008 to June 2021. The paper studies the macro-economic variables that influence the exchange rate as well.

The results from random forest model have shown that the CPI and CODC have significant importance in the behavior of the exchange rate, while GED and current accounts are not significant.

After the evaluation of the random forest model, the forecast of macro-economic indicators for 12 months was obtained from time series models. The predicted values received are placed in the random forest built model, in order to estimate the average monthly forecast of the Euro to ALL exchange rate, for July 2021 to June 2022. According to the results the average value of the exchange rate is projected to be approximately 122.4.

This study is significant since it is one of the first in the nation to use advanced modeling techniques. Despite the fact that 2020 was a significant year that had an impact on the country's social and psychological climate in addition to its economic state, the combination of random forest models and time series improves forecast performance. The model in use appears to function well and is unaffected by COVID-19.

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