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Modelling and Forecasting of EUR/USD Exchange Rate Using Ensemble Learning Approach

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***Abstract*:** *The aim of the study is to obtain an accurate result from forecasting the EUR/USD exchange rate. To this end, high-performance machine learning models using CART Ensembles and Bagging method have been developed. Key macroeconomic indicators have been also examined including inflation in Europe and the United States, the index of unemployment in Europe and the United States, and more. Official monthly data in the period from December 1998 to December 2021 have been studied. A careful analysis of the macroeconomic time series has shown that their lagged variables are suitable for model's predictors. CART Ensembles and Bagging predictive models having been built, explaining up to 98.8% of the data with MAPE of 1%. The degree of influence of the considered macroeconomic indicators on the EUR/USD rate has been established. The models have been used for forecasting one-month-ahead. The proposed approach could find a practical application in professional trading, budgeting and currency risk hedging.*

***Keywords*:** *CART-Ensembles and Bagging, machine learning, predictive model, autoregressive integrated moving average, key macroeconomic indicators.*

1. Introduction

The strength of a certain economy depends on several main macro factors, commonly called key macroeconomic indicators. These are the inflation, unemployment, gross domestic product, main interest rate, foreign exchange rate and so on. These key macroeconomic indicators are inextricably linked and the various changes in each of them most often lead to desired or undesirable consequences in the others. Any excessive changes lead to certain misbalances, which in most cases are unpredictable, highly undesirable and difficult to correct. The key macroeconomic indicators are widely used in the preparation of state budgets, they are regularly monitored to assess how the economy is performing and in case of deviation from the desired policy outcome, to press the regulators to act immediately. The main goal of any modern economy is to increase consumer welfare, to increase the national wealth and to increase the overall national production and consumption. In most cases, this means low unemployment, low inflation, low interest rates and low government debt. The most readily available expression of the stability and power of a certain economy is the strength of its currency, which is directly dependent on the changes in the minimum of the above key macroeconomic indicators. Forecasting of the foreign exchange rate movements and future values is a mandatory part of any macro financial equation, both for professional financial market participants and for those who make the budgets of countries, traders, importers and exporters of goods and services, politicians, econometricians and practitioners. In this sense, it is especially important the forecasting of the foreign exchange rates to be not only accurate but also effective.

However, analysing and forecasting of the foreign exchange rate time series is a challenging task for the scientific community due to its non-linear, complex and incorrect structural characteristics [1, 2]. According to the existing literature, research in this area is generally devoted to the development of effective forecasting approaches, which can be divided into two categories: classical econometric and statistical methods and models of Artificial Intelligence (AI). Econometric and statistical methods are widely used to predict foreign exchange rates and these methods are based on restrictive assumptions for data distribution and other specific assumptions [3, 4]. The application of this type of methods makes it difficult to detect complex nonlinear and locally nonlinear hidden dependencies in exchange rates, which in many cases leads to inaccurate forecasting. To deal with the characteristic non-stationary and high volatility of the foreign exchange rates a large number of models based on Machine Learning (ML) algorithms have been developed. In [5] a multi-layer perceptron with back-propagation error algorithm has been used for forecasting three exchange rates (EUR/USD, GBR/USD and USD/JPY) on daily, monthly and quarterly basis. Authors of [6] combine deep belief networks with conjugate gradient method to forecast weekly exchange rates, using time-lagged observations without analysing them. The prediction is good, but it is one lag late. Dunis, Laws and Sermpinis [7] use artificial neural network to forecast and trade EUR/USD exchange rates. Sermpinis et al. [8] have presented a hybrid rolling Genetic Algorithm (GA) with support vector regression for forecasting and trading of major currency pairs, where GA is applied for optimal parameter selection and feature subset combination. However, some previous research focuses only on projected capacity and demonstrates a lack of economic explanation. Liu, Pantelous and von Mettenheim [9] point out that despite the many predictive results achieved, as a rule, most of these studies are based mainly on statistical criteria for accuracy, such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE) and more. The predictive power of a certain method is undoubtedly important, although practitioners choose appropriate forecasting approaches to study only time series, without taking into account the key macroeconomic indicators.

In order to improve the accuracy of forecasting of the foreign exchange rates a powerful computer-based ensemble methods have been actively developed in recent years. Ensemble learning uses different approaches to combine multiple models, built using the same algorithm to achieve a more accurate and effective description of dependencies or classification [10, 11]. For forecasting the time series in the area of exchange rates being studied, a number of results based on ensemble learning have been published. Yu, Lai and Wang [12] propose a multistage nonlinear radial basis function (RBF) neural network ensemble forecasting model for foreign exchange rates prediction. A Conditional Generalized Variance (CGV) minimization method is proposed to select the appropriate ensemble members. In [13] clustering algorithms and kernel-based extreme learning machine are considered to build a nonlinear ensemble model for exchange rates forecasting. Sun, Wang and Wei [14] apply an ensemble deep learning approach by integrating Long-Short Term Memory (LSTM) neural network and bagging ensemble learning strategy to examine potential financial profitability of exchange rates between the US dollars against other four major currencies.

In order to achieve the most accurate forecast possible for the development of the EUR/USD foreign exchange rate, we will focus on the dependence of foreign exchange trading, taking into account the impact of the key macroeconomic indicators. The aim of this study is to build highly effective predictive ML models, suitable for practically usable forecasts.

To this purpose the AutoRegressive Integrated Moving Average (ARIMA) and CART-Ensembles and Bagging approaches are used.

2. Data and methods

2.1. Data collection

In this study, we use official data provided by the Bloomberg professional terminal. The dataset is arranged by month and the time series covers the period December 1998-December 2021 or a total of $n = 277$ samples. The variables and their descriptive statistics are given in Table 1. Here $Y =$ EUR/USD_FX_RATE will be considered as a dependent variable. The macroeconomic indicators are denoted by $X_1, X_2, ..., X_8$ and will be used to construct the predictors. The specificity of time series data in Table 1 is that they are measured simultaneously, which makes it difficult to forecast in real time.

Table 1. Descriptive statistics of the data used[1]

Variable	Description	Measure	Mean	Median	Std. deviation
Y	EUR/USD_FX_RATE	Rel. units	1.1997	1.1996	0.1603
X_1	EUROZONE_UNEMPLOYMENT	%	9.3401	9.1000	1.3455
X_2	USA_UNEMPLOYMENT	%	5.8769	5.4000	1.9333
X_3	EUROZONE_INFLATION	index	92.6192	93.3100	9.6647
X_4	USA_INFLATION	%	2.2415	2.1000	1.3511
X_5	ECB_INTEREST_RATE	%	0.8529	0.2500	1.2893
X_6	FED_INTEREST_RATE	%	1.8673	1.2500	1.9222
X_7	EUR_10Y_BUND_YIELD	%	2.4485	3.0250	1.9060
X_8	USD_10Y_BOND_YIELD	%	3.2976	3.1435	1.4196

[1] The percentage is set on a monthly basis.

2.2. Methods and performance measures for model evaluation

We will perform the modelling in two main stages, namely feature selection and model construction. In the first stage we use the well-known parametric univariate Box-Jenkins ARIMA [15] and the unit root tests to examine all initial time series.

After defining relevant predictors (i.e., features) for modelling and forecasting of Y, we will apply the powerful ML method CART-Ensembles and Bagging (EBag). This method has been developed by Breiman [16] using bootstrap aggregation (known also as bagging). By its nature, it creates an ensemble of a pre-set number of independent binary decision trees using the Classification And Regression Tree (CART) algorithm [17] for different perturbed samples from the original dataset. For the case of regression, the predictive ensemble model is the arithmetic mean of the predictions of its component trees.

In order to evaluate the models we use the following statistical measures: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and coefficient of determination R^2:

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2}{n}}, \quad \text{MAPE} = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{P_k - Y_k}{Y_k}\right|, \tag{1}$$

$$R^2 = \frac{\left\{\sum_{k=1}^{n}\left(P_k - \bar{P}\right)\left(Y_k - \bar{Y}\right)\right\}^2}{\sum_{k=1}^{n}\left(P_k - \bar{P}\right)^2 \sum_{k=1}^{n}\left(Y_k - \bar{Y}\right)^2}, \tag{2}$$

where Y_k and P_k are the values of dependent and predictor variables, respectively, and $\bar{Y}$, $\bar{P}$ are their means, n is the sample size.

3. Modelling results

3.1. Feature selection, using univariate ARIMA

After check-up of the necessary assumption of normality of the initial independent time series $Y, X_1, X_2, ..., X_8$ from Table 1 the univariate ARIMA analysis is performed for each of them [15].

Table 2. Statistics of the obtained univariate ARIMA models for feature selection

Variable	Description	ARIMA $(p, d, q)_s$	Ljung-Box statistic	R^2
Y	EUR/USD_FX_RATE	$(0, 1, 0)_{12}$	0.103	0.956
X_1	EUROZONE_UNEMPLOYMENT	$(0, 1, 9)_{12}$	0.198	0.996
X_2	USA_UNEMPLOYMENT	$(0, 1, 1)_{12}$	0.987	0.867
X_3	EUROZONE_INFLATION	$(0, 1, 6)_{12}$	0.071	1.000
X_4	USA_INFLATION	$(0, 1, 1)_{12}$	0.202	0.946
X_5	ECB_INTEREST_RATE	$(0, 1, 3)_{12}$	0.056	0.989
X_6	FED_INTEREST_RATE	$(0, 1, 9)_{12}$	0.684	0.991
X_7	EUR_10Y_BUND_YIELD	$(0, 1, 3)_{12}$	0.740	0.991
X_8	USD_10Y_BOND_YIELD	$(0, 1, 0)_{12}$	0.383	0.969

The obtained models are shown in Table 2. The models are written in the standard form ARIMA$(p, d, q)_s$, where p is the number of autoregressive terms, d is the number of trends, q is the number of moving average terms, s=12 is the seasonality. The Ljung-Box (L-B) statistics of all models are insignificant, therefore, we can assume the models are adequate [15]. Also, the models have excellent performance with high R^2. The most important information for us from Table 2 is that there is a trend $d=1$ for all variables and zero AutoRegressive (AR) member ($p=0$).

3.2. Results from the unit root test for the initial time series and their differenced series

To check independently the existence of the trends presented in Table 2 we will examine the time series for the presence or absence of a unit root. Let us consider a simple AR(1) model

(3) $$T_{i+1} = \varphi_1 T_i + Z_i ,$$

where T is a time series, and Z is the residual series of this approximation. A unit root is present if $\varphi_1 = 1$. The model is non-stationary in this case, or $d \geq 1$. In order to justify the presence of unit root two standard statistical tests – Dickey-Fuller F-test and Phillips-Perron F-test were established. The null hypothesis H_0 means that the time series is stationary, in other words – a small P-value (Probability value) suggests that the presence of a unit root is unlikely. The alternative hypothesis H_a means non-stationarity and indicates the presence of a trend.

Table 3 presents the results of the unit root tests for the initial time series, obtained with Wolfram Mathematica software [18] at the 5% confidence level. Table 3 shows that all P-values for the initial variables are insignificant, so the null hypothesis H_0 of the unit root tests could be rejected and $\varphi_1 = 1$. Therefore, all initial time series $Y, X_1, X_2, \ldots, X_8$ are not stationary and have a trend of at least first order, or $d \geq 1$.

Table 3. Results from the unit root tests of the initial time series

Statistic	Y	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Dickey-Fuller F test									
t statistic	–0.137	–0.326	–1.703	0.370	–0.747	–2.755	–2.380	–1.302	–1.411
P-value	0.6523	0.6094	0.3663	0.7780	0.5211	0.2941	0.2886	0.4238	0.4066
Phillips-Perron F test									
t statistic	–0.146	–0.358	–1.447	0.369	–3.247	–4.150	–3.257	–1.345	–1.413
P-value	0.6501	0.6020	0.4012	0.7779	0.2155	0.1606	0.2148	0.4171	0.1803

For the differenced series $DX_1, DX_2, \ldots, DX_8$, calculated by

(4) $$DT_i = T_i - T_{i-1},$$

the corresponding indices of the unit root tests are given in Table 4. The results in this table clearly solve the unit root problem, as all P-values are practically zero. Therefore, in this case, the null hypothesis H_0 could not be rejected and these variables are assumed to be stationary.

Table 4. Results from the unit root tests of the differenced time series

Statistic	DY	DX_1	DX_2	DX_3	DX_4	DX_5	DX_6	DX_7	DX_8
Dickey-Fuller F test									
t-statistic	–270.90	–134.44	–267.36	–137.24	–161.29	–198.77	–213.56	–265.72	–257.70
P-value	9×10^{-13}	3×10^{-10}	1×10^{-12}	2×10^{-10}	6×10^{-11}	1×10^{-11}	6×10^{-12}	1×10^{-12}	1×10^{-12}
Phillips-Perron F test									
t-statistic	–278.33	–145.39	–241.03	–103.82	–147.04	–242.58	–263.98	–270.01	–244.88
P-value	8×10^{-13}	2×10^{-10}	2×10^{-12}	2×10^{-9}	1×10^{-10}	2×10^{-12}	1×10^{-12}	1×10^{-12}	2×10^{-12}

The results of the unit root tests confirm the trends in the ARIMA models from Table 2. Thus, it has been found that the lagged time series of $X_1, X_2, ..., X_8$, i.e.,

(5) $$LT_1 = T_1,\ LT_i = T_{i-1},\ i = 2,3,...,n,$$

are suitable for building ensemble regression models.

This practically means that the values of the time series for each current month are almost equal to the value of the previous one, ignoring the small members of the models. These results suggest to select lagged variables for predictors in the ensemble models in the next stage. Using $\mathrm{LX}_1, \mathrm{LX}_2, ..., \mathrm{LX}_8$ would allow forecasting the value of the dependent time series EUR/USD_FX_RATE for any current month using the data of the macroeconomic series of the previous months. In this approach, our model will find its practical application.

3.3. Building and evaluation of the CART-Ensembles and Bagging (EBag) models

In order to build EBag models we construct the necessary lagged variables of $X_1, X_2, ..., X_8$. We denote them by $\mathrm{LX}_1, \mathrm{LX}_2, ..., \mathrm{LX}_8$. They will be introduced into four groups according to the type of their information. In the process of modelling, a large number of models were built, by varying their hyperparameters. From them was chosen the number of trees in the ensemble from 10, 20, 30, 40; the type of training with Cross-Validation (CV) – from 10-fold CV and 15-fold CV; minimum cases in the terminal node of the tree – 5 and 10. The models with the best performance are EBag models with 40 trees, standard 10-fold CV and minimum cases in a terminal node set to 5.

In order to demonstrate a more realistic situation, the last value Y_{277} (for December 2021), which was predicted by the constructed models, was removed from the dependent time series Y, EUR/USD_FX_RATE and was used for verification.

Table 5 shows the results achieved, where the models are denoted by $G1$, $G2$, $G3$, and $G4$. The combination of predictor groups of lagged variables is recorded in column 2 of Table 5. The first predictor group for the $G1$ model includes only data with unemployment numbers in EU and USA. For the next $G2$ model, the variables for the inflation data in EU and USA have been added. In addition to the variables introduced so far, the $G3$ model also uses data for the base interest rates of ECB and FED. For the latest $G4$ model, data on the yield of EU and USA 10 years' securities have been added.

Table 5. Statistics of the CART-Ensembles and Bagging models

Model	Predictors	RMSE	MAPE	R^2
*G*1	LX_1, LX_2	0.0408	0.0222	0.9377
*G*2	LX_1, LX_2,LX_3,LX_4	0.0182	0.0108	0.9874
*G*3	LX_1, LX_2, LX_3, LX_4, LX_5, LX_6	0.0185	0.0108	0.9868
*G*4	LX_1, LX_2, LX_3, LX_4, LX_5, LX_6, LX_7, LX_8	0.0174	0.0103	0.9884

The statistics in Table 5 show that the models are improving with the addition of the next group of predictors. The last three models can be considered almost equally good. Very good performance of the models was achieved, with coefficient of determination of about $R^2 = 98.8\%$, RMSE=0.017, MAPE=1%.

In particular, for the last value Y_{277} =1.1370 the forecasts of EBag models are: 1.1642 (*G*1), 1.1391 (*G*2), 1.1349 (*G*3), 1.1360 (*G*4), respectively. The predicted values of models *G*2, *G*3, and *G*4 fit the original data with up to 99%, a forecast that in the financial world is equal to millions of US Dollars profit.

Fig. 1 illustrates the sequence plot of the original data for EUR/USD_FX_RATE with those predicted by model *G*4.

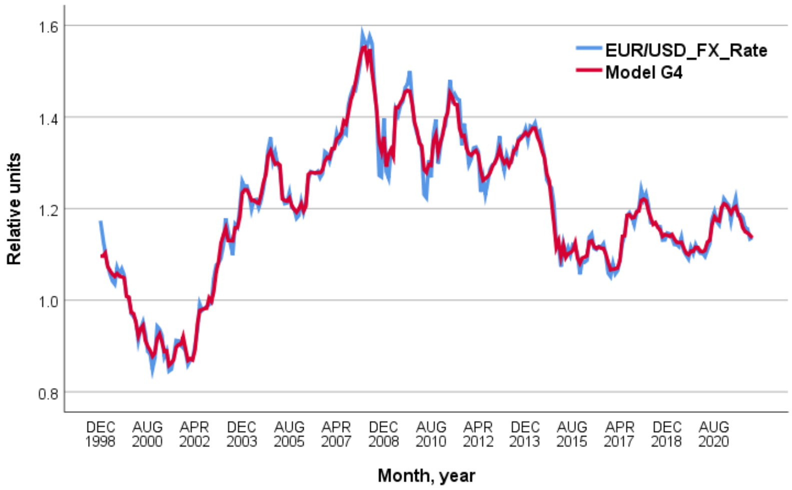

Fig. 1. The original data for EUR/USD_FX_RATE against the forecasts of *G*4 model

The next Fig. 2 shows the quality of fitting the original data for EUR/USD_FX_RATE compared to the predictions of model *G*4 with 5% confidence intervals. A very good approximation is observed, including that of the extreme values.

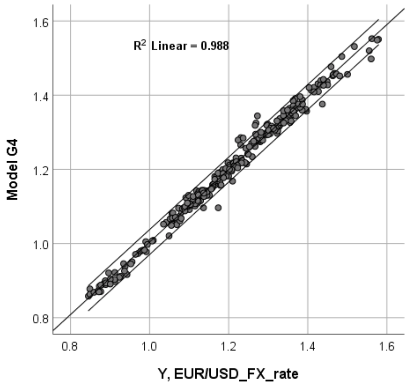

Fig. 2. Scatter plot of the EUR/USD_FX_RATE and predictions from the
*G*4 EBag model

3.4. Variable importance

The EBag method allows to determine the relative influence of predictors in the model. For the selected model *G*4 this influence can be seen in Fig. 3. The first variable is considered to have weight of 100 scores, and others are relative to it. In our case the biggest relative importance has the EU inflation (100), followed by EUR_10Y bund yield (88), USD_10Y bund yield (60), and ECB interest rate (53).

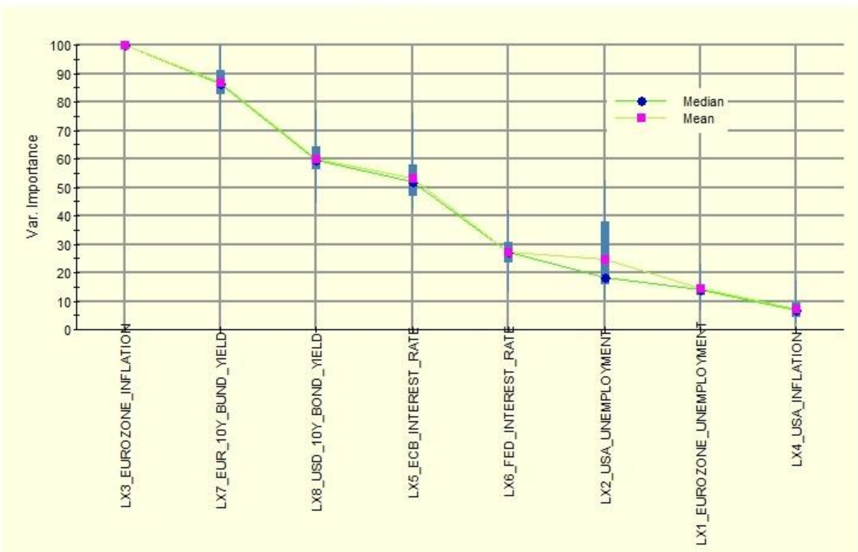

Fig. 3. Relative variable importance of predictors in model *G*4

3.5. Reliability evaluation of the forecasts

Following [19, 20], we need to evaluate the reliability of all forecasting models. To this end the Auto-Correlation Function (ACF) plot for checking the existence of the autocorrelation process in the model's residuals could be performed. In other words, we need to show whether the residuals are identically distributed and asymptotically independent, and no serial correlation has remained in the model errors.

Fig. 4 shows the ACF of the *G*4 model's residuals. There are negligible deviations outside the confidence intervals. We can conclude that the *G*4 model is reliable and can predict the EUR/USD rate reasonably.

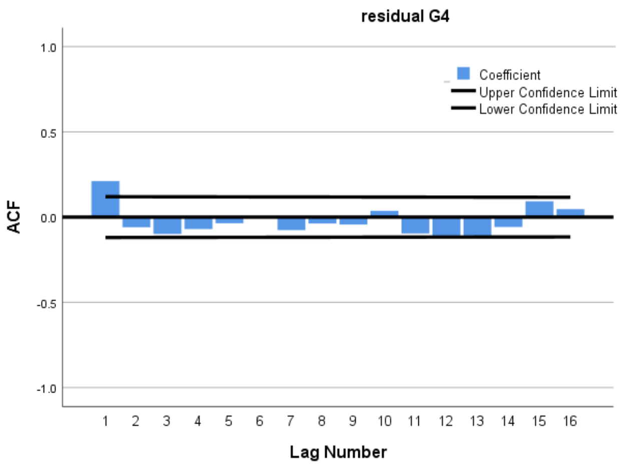

Fig. 4. Autocorrelation function of *G*4 residuals

4. Conclusion

In this study, a high performance of the CART-Ensembles and Bagging method for foreign exchange forecasting has been demonstrated. As far as the authors know, in this field, it has not been used so far and its possibilities have not been studied. The contribution of this paper is the use of this method, combined with the preliminary careful analysis and selection of relevant independent predictors. It has been shown that with the help of the Box-Jenkins methodology of univariate ARIMA, their lagged variables can be used to predict the dependent variable one month ahead.

As a result, we have established the dependence of the foreign exchange rates from various macroeconomic indicators. The numbers of the inflation, the base interest rates related to its management, the unemployment data as a part of the economic development of a given economy and its debt prices are deeply connected. Therefore, the achievement of accurate forecast of the future values of the foreign exchange rate cannot be made without taking into consideration the other key macroeconomic indicators.

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