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Vasyl PRYIMAK, Bohdan BARTKIV, Olga HOLUBNYK
Ivan Franko National University of Lviv

FORECASTING THE EXCHANGE RATE OF THE UKRAINIAN HRYVNIA USING MACHINE LEARNING METHODS

This article describes the concept of currency exchange rate and the typology of various factors that influence it. A multifactor regression model was constructed to investigate the influence of factors on the exchange rate of the Ukrainian hryvnia and to forecast the dynamics of this rate based on the studied factors using Data Science technologies.

The purpose of this work is to study the peculiarities of the formation of the exchange rate of the Ukrainian hryvnia, the characteristics of the influence of various external factors on this rate, and the creation of an effective forecasting model of the Ukrainian national currency rate, based on a certain number of fundamental financial and economic factors that influence this rate.

Macroeconomic indicators that theoretically have an impact on the dynamics of the currency exchange rate were chosen to build the model. Data on the exchange rate of the Ukrainian hryvnia to the US dollar and economic indicators for selected factors were collected from 2010 to September 2022. During the implementation of the task, the collected data was processed, brought into a uniform form, and normalized. Machine learning methods were used for regression modeling, specifically the XGBoost gradient boosting method.

As a result, a retrospective forecast of the Ukrainian hryvnia exchange rate was obtained, based on factor variables, and an estimate of the impact of each selected feature on the currency exchange rate was calculated. The scientific novelty of this work lies in the application of modern machine learning methods and technologies for the analysis, modeling, and forecasting of the exchange rate of the Ukrainian national currency.

The practical significance of this article lies in the possibility of using the proposed approaches to forecasting the exchange rate of the Ukrainian hryvnia with the use of machine learning methods by all interested parties, including financial institutions of Ukraine, to achieve stability of the national currency, which in turn will affect the development of the national economy as a whole and the welfare of the population of the country.

Keywords: exchange rate, gradient boosting, regression analysis, machine learning, forecasting, Ukrainian hryvnia, Data Science.

Василь ПРИЙМАК, Богдан БАРТКІВ, Ольга ГОЛУБНИК
Львівський національний університет імені Івана Франка

ПРОГНОЗУВАННЯ ВАЛЮТНОГО КУРСУ УКРАЇНСЬКОЇ ГРИВНІ З ВИКОРИСТАННЯМ МЕТОДІВ МАШИННОГО НАВЧАННЯ

У даній статті описано поняття валютного курсу та типологію різноманітних чинників впливу на нього. Побудовано багатофакторну регресійну модель для дослідження впливу факторів на курс української гривні та спрогнозовано динаміку цього курсу на основі досліджуваних факторів.

Метою даної роботи є дослідження особливостей формування валютного курсу української гривні, характеристика впливу різноманітних зовнішніх факторів на цей курс та створення за допомогою Data Science технологій ефективної моделі прогнозування курсу української національної валюти, яка ґрунтується на певній кількості фундаментальних фінансово-економічних факторів впливу на цей курс.

Для побудови моделі обрано макроекономічні показники, які теоретично мають вплив на динаміку валютного курсу. Для статистичного аналізу та подальшого моделювання зібрано дані про валютний курс української гривні до долара США та економічні показники для обраних факторних ознак за період з 2010 по вересень 2022 рр. В ході реалізації поставленого завдання проведено обробку, зведення до єдиної форми та нормалізацію зібраних даних. Для безпосереднього моделювання використано методи машинного навчання для задачі регресії, а саме метод градієнтного бустингу (XGBoost). В результаті отримано ретроспективний прогноз курсу української гривні, базований на факторних змінних і розраховано оцінку впливу кожної вибраної ознаки на валютний курс.

Наукова новизна даної роботи полягає у застосуванні сучасних методів та технологій машинного навчання для аналізу, моделювання та прогнозування курсу української національної валюти.

Практична значимість цієї статті полягає у можливості використання запропонованих у ній підходів до прогнозування валютного курсу української гривні з застосуванням методів машинного навчання всіма зацікавленими сторонами, зокрема фінансовими установами України, задля досягнення стабільності національної грошової одиниці, що у свою чергу вплине на розвиток національної економіки у цілому та добробут населення держави.

Ключові слова: валютний курс, градієнтний бустинг, регресійний аналіз, машинне навчання, прогнозування, українська гривня, Data Science.

Introduction

The exchange rate, despite being a measure of the value of the national currency expressed in monetary units of other countries, is also an indicator of the domestic economic situation, reflecting the main trends in the development of the national economy and influencing the redistribution of national income between countries.

Significant volatility in the national currency exchange rate can have negative consequences for export potential, foreign trade, and the economy as a whole. Therefore, the key task of state regulation of the monetary system in the conditions of a market economy is to study the factors that affect the exchange rate and react promptly to the main trends in the economy to ensure its stability.

Macroeconomic forecasting of economic indicators and processes, including forecasting of exchange rates, is a complex task. There are currently no macroeconomic models that would have the functionality to make reliable macroeconomic forecasts of economic development and the exchange rate of the national currency. Therefore, the development of such models is always an important and relevant problem.

The article examines the peculiarities of the formation of the exchange rate and analyzes the impact of various external factors on the exchange rate of the Ukrainian hryvnia. Using machine learning methods, a regression model, namely the gradient boosting model (XgBoost), was built to study the impact of the given factors on the exchange rate of the Ukrainian hryvnia. Modern Data Science technologies for data analysis and solving tasks of economic-mathematical modeling and socio-economic forecasting are considered.

Related works

This work analyzes the works of Ukrainian scientists on the factors influencing the exchange rate in general, and the exchange rate of the Ukrainian hryvnia in particular. The authors of scientific papers [1-3] define the concept of exchange rate and classify the factors that influence its formation. In the work [4], the author presents theoretical methods for predicting currency exchange rates. The basic principles of macroeconomic modeling and forecasting of the exchange rate in Ukraine are studied in the monograph [5]. In scientific papers [6-9], the authors investigate the factors influencing the formation of the exchange rate in Ukraine and analyze the degree of influence of various indicators on the exchange rate of the Ukrainian hryvnia as an integral part of the national economy.

The author of the scientific article [10] considers the main directions of using Data Science algorithms in central banks, including predicting macroeconomic and financial variables. The theoretical foundations of Data Science technologies and their application in economic-mathematical modeling are described in works [11-13]. The characteristics of machine learning algorithms for solving regression, classification, and forecasting tasks are presented in articles [14-15]. The authors of scientific papers [16-18] describe the principle of the gradient boosting modeling algorithm, its specificity, and the features of its application.

However, modeling and forecasting of the exchange rate are always relevant tasks, as new data appears every day, and trends in the economy change. Therefore, the purpose of this work is to study the peculiarities of the formation of the exchange rate of the Ukrainian hryvnia, the characteristics of the influence of various external factors on this rate, and to create an effective model for predicting the exchange rate of the Ukrainian national currency using Data Science technologies, based on fundamental financial and economic factors that affect it.

Presenting main material

The exchange rate is determined by the market interaction of demand and supply under conditions of perfect competition, reflecting a complex set of factors that directly and indirectly affect the exchange rate of both the national economy and international economic relations.

The multifactorial nature of the exchange rate reflects its connection with other economic categories, such as value, price, money, interest rates, and more. In modern conditions, the exchange rate is formed under the influence of demand and supply in the foreign exchange market, but along with the state of the balance of payments, its size is influenced by a large number of other factors, such as the level and dynamics of inflation, the amount of money in circulation, interest rates, GDP volumes, and growth rates, the level of development of the financial market, political and psychological factors, and much more. As a result, the formation of the exchange rate at the present stage is considered a multifactorial process. Modern researchers of the process of exchange rate formation group numerous exchange rate factors according to certain characteristics. In particular, factors are divided into three groups: fundamental, technical, and force majeure. Fundamental factors are key macroeconomic indicators of the state of the national economy that affect foreign exchange market participants and the exchange rate level.

Figure 1 provides a more detailed demonstration of the variety of factors that influence the exchange rate. Such a distribution is quite conditional because some components cannot be unequivocally attributed to a certain group, as most of them are interrelated. However, this can facilitate the perception of the entire complex of components forming the exchange rate of the currency.

Among the social and political factors, one can distinguish the political situation in the country, the level of trust of the population in the banking system, the presence of a "black market," the level of financial literacy of the population, and others. Additionally, to some extent, the psychological factor that shapes public attitudes based on forecasts of currency exchange rates spread by rumors, forecasts, and speculation in the media, which generate excitement in the currency market, also influences the exchange rate.

In the current conditions of an unstable economic situation, such a factor as speculative capital flows deserves special attention. This factor can affect the dynamics of the exchange rate if the central bank tries to keep it at a certain level against the action of market forces. If the exchange rate of a certain national currency tends to decrease, firms and banks try to sell it in advance in exchange for more stable currencies, counting on conducting a reverse operation at a lower rate after a certain period. The difference, therefore, forms speculative income. These operations significantly weaken the exchange rate of the national currency [8].

A specific factor of influence is the technical analysis of the foreign exchange market, which is based on predicting the exchange rate based on the quantitative analysis of available factors. Studying data on previous currency quotes allows us to identify certain patterns of currency formation and therefore show probable changes in exchange rates in the future, both in terms of their directions, volumes, and speed. According to this concept, predicting future levels of currency quotes depends on their dynamics in the past [4].

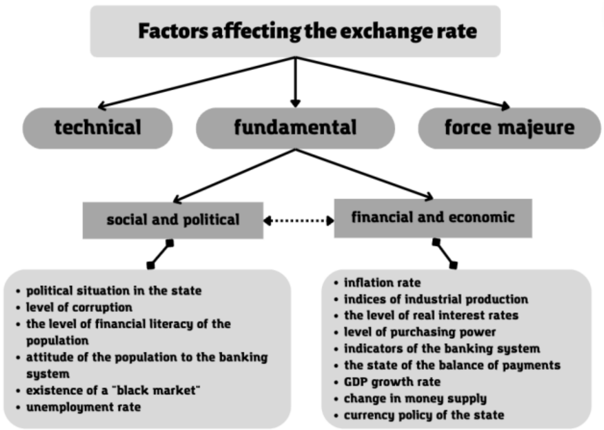

Fig. 1. Visualization of factors affecting the exchange rate

The components of the financial-economic factors influencing the exchange rate of the national currency include the main macroeconomic indicators of the country's economy, such as the inflation rate, GDP, dynamics of the money supply, various production indices, and many other indicators.

In addition to fundamental and technical factors, the impact of which can be somewhat predictable, there are also force majeure factors that can make significant adjustments to the dynamics of the exchange rate. Such force majeure factors include wars, outbreaks of epidemics, unforeseen financial and economic crises, natural disasters, technological catastrophes, and so on. All these factors have a negative impact on the stability of the national currency, as overcoming any problem requires significant resources.

To build a model for forecasting the exchange rate, the programming language Python was used. Python is a high-level object-oriented programming language used for web application development, software development, and machine learning. The Python software is presented in the form of models, which can be assembled into packages [19].

The Scikit-learn library was used for direct data analysis. It is a free machine learning software library for the Python programming language that provides functionality for creating and training various classification, regression, and clustering algorithms, and works in conjunction with NumPy. NumPy is an extension of the Python language that adds support for large multi-dimensional arrays and matrices. The Pandas software library was used for data manipulation. The Matplotlib and Seaborn libraries were used for two-dimensional or three-dimensional data visualization, providing capabilities for building graphs, scatter plots, bar and pie charts, as well as animated images.

To build a regression model for predicting the exchange rate of the Ukrainian hryvnia, data was collected on various financial and economic factors influencing the exchange rate over the period from 2010 to September 2022. Specifically, the following features were used (the encrypted name of the feature is indicated in parentheses, which is further used in the captions of the graphs and diagrams):

- Producer Price Index (PPI) – an indicator of the average level of wholesale price changes for raw materials, materials, and intermediate goods sold by national producers;
- The Inflation Index, or Consumer Price Index (CPI) – is an indicator that characterizes changes in the overall price level of goods and services that the population buys for non-production consumption. The model also uses the Consumer Price Index for the corresponding month of the previous year (inflation_p) and the Consumer Price Index for December of the previous year (inflation_12);
- Foreign Exchange Reserves (FX Reserves) – external highly liquid assets under the supervision of the state (the National Bank of Ukraine and the Government of Ukraine);
- Gross Domestic Product per capita in US dollars (gdp_pers_usd);
- Unemployment rate (unemployment) – a quantitative indicator that is determined as the ratio of the number of unemployed to the total number of the economically active working population of the country (region, social group) and is measured in percentage;
- Consolidated Balance of Payments in US dollars (BOP) – a statistical report that provides systematic information on the external economic operations of the country's residents with non-residents for a certain period;
- Real Wage Index (RSI) – an indicator that characterizes the change in the purchasing power of nominal wages;
- Net Foreign Direct Investment (FDI) balance;
- State Budget performance balance (gov_budg) or budget deficit;
- Total State Debt in US dollars (state_debt_usd);
- Balance of External Trade (int_trade) – the difference between exports and imports.

The data was collected from open sources, namely the website of the State Statistics Service of Ukraine [20] and the website of the Ministry of Finance [21]. The model also takes into account the factor of currency sales volume on the interbank currency market of Ukraine ('interbank'), data taken from the official website of the National Bank of Ukraine [22]. Since information on currency sales volumes on the interbank market is provided daily, it was summed up on a monthly basis to add to the table of data on other factors.

The official exchange rate of the Ukrainian hryvnia to the US dollar established by the National Bank of Ukraine was taken as the resulting variable. Data on the exchange rate is also provided daily, so it was aggregated monthly using a built-in function in Python. The dynamics of the Ukrainian hryvnia exchange rate for the studied period are presented in Fig. 2.

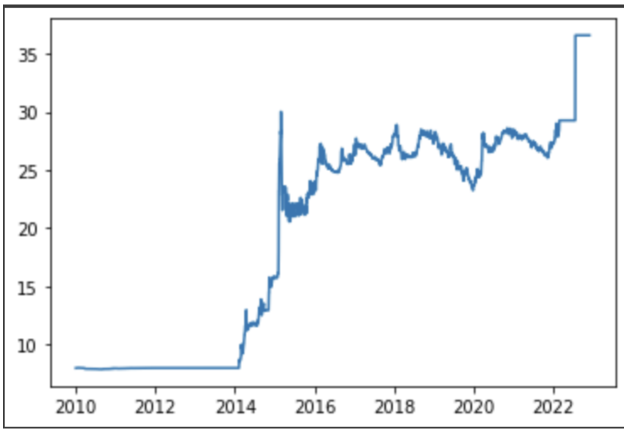

Fig.2. The official exchange rate of the Ukrainian hryvnia to the US dollar

After collecting the data and importing it into the Python programming environment, data processing was carried out. Since some data, such as GDP per capita or unemployment rate, is provided annually, while the aggregated balance of payments and the direct foreign investment balance are provided quarterly, there were many "empty" values in this data set. To solve this task, polynomial interpolation was used. The peculiarity of this type of interpolation is the construction of a polynomial P_n (x) of a degree less than or equal to n, which takes values of $f(x_i)$ at the interpolation nodes x_0, x_1, ..., x_n. The system of equations that determines the coefficients of such a polynomial has the form:

$$P_n(x_i) = a_0 + a_1 x_i + a_2 x_i^2 + \dots + a_n x_i^n = f(x_i), i = 0,1, \dots, n \tag{1}$$

The statistics for the numerical columns (count, mean, standard deviation, minimum, maximum, and quantiles) are shown in Figure 3.

	ppi	fx_reserves	gdp_pers_usd	unemployment	bop	rsi	fdi	gov_budg	state_debt_usd	int_trade	inflation_12	inflation_p	inflation	exrate	interbank
count	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000	124.000000
mean	101.457443	20446.390645	3298.969816	10.205075	-213.830798	100.316129	670.183490	-36924.237903	76971.708811	-137975.599088	107.847581	110.212903	101.052419	21.934865	10186.924758
std	2.678052	6277.286724	733.444726	4.226107	1944.509634	6.808834	657.282772	73617.475860	11625.949094	85936.523909	10.522144	11.277577	1.865888	7.783870	8270.621035
min	96.200000	5625.310000	2115.000000	7.600000	-8360.000000	80.300000	-1553.000000	-418558.700000	60076.333333	-311183.000000	99.400000	100.000000	98.700000	7.990777	2858.050000
25%	100.000000	15533.125000	2641.563699	8.892778	-640.122283	97.300000	384.379348	-43683.100000	68696.843750	-182669.520492	101.300000	103.600000	100.000000	15.404735	5045.502500
50%	101.250000	20318.085000	3490.625479	9.600000	243.993651	100.400000	626.228261	-20575.550000	74815.431667	-113082.358904	104.250000	107.400000	100.800000	26.038961	6735.270000
75%	102.600000	25805.565000	3856.354795	9.970556	853.029891	103.175000	1000.420330	-2317.425000	82945.761042	-66695.943836	109.500000	109.425000	101.325000	27.181653	10860.962500
max	112.500000	31614.070000	4834.300000	35.000000	3782.000000	121.500000	2386.000000	38470.300000	123612.517241	-39475.000000	143.300000	147.100000	114.000000	36.568600	45147.060000

Fig. 3. The statistics for the numerical columns of the input data

In Figure 4, a correlation matrix of relationships between factors is presented (warmer colors indicate stronger relationships). By analyzing this matrix, we can observe the correlation between factors and the resulting feature. There is a strong negative correlation between the exchange rate and the volume of currency sales in the interbank foreign exchange market of Ukraine. It is also worth noting a fairly strong relationship between the resulting feature and the level of government debt. The exchange rate has a moderate correlation with factors such as the unemployment rate and foreign trade balance (both negative).

	ppi	fx_reserves	gdp_pers_usd	unemployment	bop	rsi	fdi	gov_budg	state_debt_usd	int_trade	inflation_12	inflation_p	inflation	exrate	interbank
ppi	1.000000	-0.036768	0.036742	-0.000524	-0.126987	-0.209618	-0.074206	0.042486	0.141598	0.127140	0.041958	0.107166	0.365768	0.189759	-0.211721
fx_reserves	-0.036768	1.000000	0.778584	0.098460	0.187987	0.046797	0.179845	-0.241109	0.506477	0.215893	-0.496570	-0.608674	-0.349499	0.022933	0.340619
gdp_pers_usd	0.036742	0.778584	1.000000	0.098914	-0.159904	-0.054161	0.105592	-0.266671	0.493679	0.512438	-0.374167	-0.462272	-0.122959	-0.255122	0.528621
unemployment	-0.000524	0.098460	0.098914	1.000000	-0.472586	-0.158106	-0.250929	-0.851443	0.663968	0.015726	0.205235	0.154151	0.158348	0.372680	-0.274529
bop	-0.126987	0.187987	-0.159904	-0.472586	1.000000	0.215657	0.146087	0.390399	-0.151850	-0.296373	-0.108229	-0.162563	-0.360512	0.161601	-0.029693
rsi	-0.209618	0.046797	-0.054161	-0.158106	0.215657	1.000000	0.095579	-0.088620	-0.091274	-0.086059	0.098253	-0.085316	-0.216852	-0.000203	0.026016
fdi	-0.074206	0.179845	0.105592	-0.250929	0.146087	0.095579	1.000000	0.217265	-0.255498	-0.031917	-0.053450	-0.021984	-0.226006	-0.280802	0.357310
gov_budg	0.042486	-0.241109	-0.266671	-0.851443	0.390399	-0.088620	0.217265	1.000000	-0.636287	-0.187391	-0.113721	0.014013	-0.044955	-0.229162	0.062365
state_debt_usd	0.141598	0.506477	0.493679	0.663968	-0.151850	-0.091274	-0.255498	-0.636287	1.000000	0.091418	-0.065932	-0.138766	0.018425	0.619703	-0.260376
int_trade	0.127140	0.215893	0.512438	0.015726	-0.296373	-0.086059	-0.031917	-0.187391	0.091418	1.000000	0.097168	0.074709	0.134878	-0.360796	0.340220
inflation_12	0.041958	-0.496570	-0.374167	0.205235	-0.108229	0.098253	-0.053450	-0.113721	-0.065932	0.097168	1.000000	0.863135	0.323193	0.137007	-0.367634
inflation_p	0.107166	-0.608674	-0.462272	0.154151	-0.162563	-0.085316	-0.021984	0.014013	-0.138766	0.074709	0.863135	1.000000	0.440099	0.193653	-0.428233
inflation	0.365768	-0.349499	-0.122959	0.158348	-0.360512	-0.216852	-0.226006	-0.044955	0.018425	0.134878	0.323193	0.440099	1.000000	0.121625	-0.266260
exrate	0.189759	0.022933	-0.255122	0.372680	0.161601	-0.000203	-0.280802	-0.229162	0.619703	-0.360796	0.137007	0.193653	0.121625	1.000000	-0.774988
interbank	-0.211721	0.340619	0.528621	-0.274529	-0.029693	0.026016	0.357310	0.062365	-0.260376	0.340220	-0.367634	-0.428233	-0.266260	-0.774988	1.000000

Fig. 4. The correlation matrix of relationships between the factors

To ensure that machine learning algorithms can work correctly with data, it is necessary to normalize them. Data normalization can be done simply by scaling them into a certain range (usually from 0 to 1), if their distribution is similar to a Gaussian distribution. In cases where the data is not normally distributed, normalization is advisable. A normal distribution of data improves the numerical stability of the model and can speed up the model training process [23].

Using the Seaborn library for data visualization, histograms were constructed for each feature to look at the data distribution. For features that did not have a bell-shaped curve distribution, normalization was performed using the Box-Cox power transformation method [24]. Examples of normalization for some of the factor variables are demonstrated in Figures 5-7.

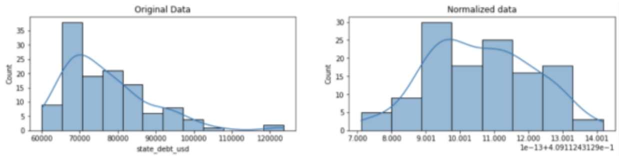

Fig. 5. Normalization of data distribution for the "state_debt_usd" indicator

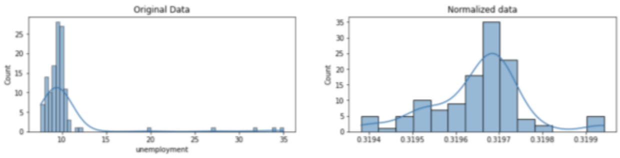

Fig. 6. Normalization of data distribution for the “unemployment” indicator

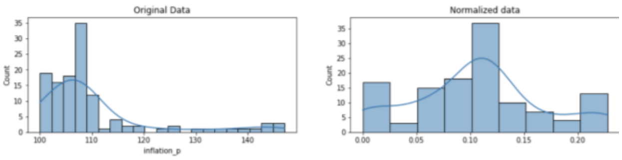

Fig. 7. Normalization of data distribution for the “inflation_p” indicator

For other features that have a similar bell-shaped distribution, standardization was performed to bring the scale of the input data into one range. This task was performed using the MinMaxScaler function (formula 2), which scaled the data into a range of 0 to 1.

$$X = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{2}$$

To decode the data later, two separate scalers were used for X (predictor variables) and Y (target variable).

The next step in data processing was the detection and handling of outliers, as they can negatively affect statistical analysis and the process of training a machine learning algorithm, leading to a decrease in accuracy. An outlier is an observation in the data set that is far from the rest of the observations. This means that the outlier is significantly larger or smaller than the other values in the set. Outliers for the given features can be seen in the histograms of the data distribution. Outliers can also be conveniently identified using box plots.

Figure 8 shows box plots for four indicators, with points that are outliers and do not fall within the range of other observations, meaning they are not close to the quartiles. To remove these outliers, a function was written that sets them equal to a certain quartile, which is manually selected.

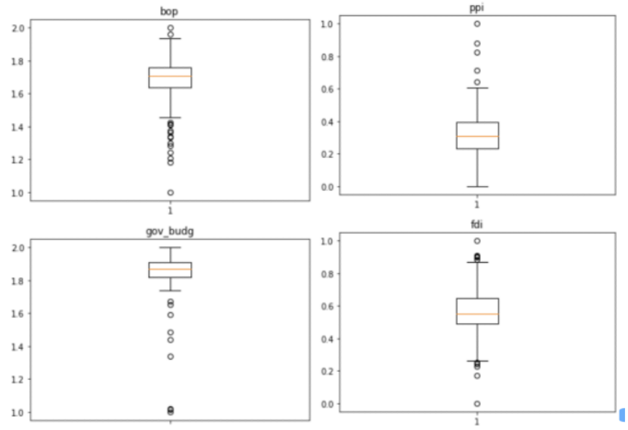

Fig. 8. Visualization of the distribution of variable values using box plots for four factors

Figure 9 shows box plots of the same factor variables, but after outliers have been corrected. As can be seen, there is no longer such a strong data spread.

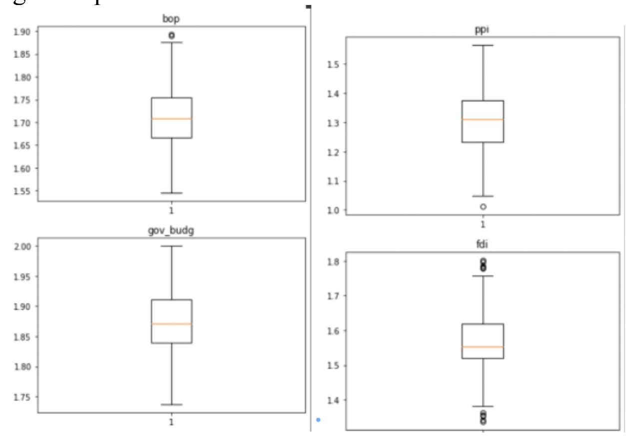

Fig. 9. Visualization of the distribution of variable values using box plots after outlier correction

The model was built using the Extreme Gradient Boosting (XGBoost) method, which is a scalable machine learning library with distributed decision trees and gradient boosting. It is a leading machine learning library for regression, classification, and ranking tasks. Decision trees create a model that predicts a label by evaluating decision tree questions about the if-then-else function, true/false, and evaluating the minimum number of questions needed to estimate the probability of making the correct decision. Gradient Boosted Decision Trees (GBDT) is a decision tree ensemble learning algorithm similar to random forests for classification and regression. Ensemble learning algorithms combine multiple machine learning algorithms to obtain a better model. Gradient boosting is an extension of boosting, where the process of additive generation of weak models is formalized as a gradient descent algorithm over the target function. Gradient boosting sets target outcomes for the next model to minimize errors. The target outcomes for each case are based on the error gradient (hence the name gradient boosting) concerning the prediction. The final prediction is the weighted sum of all tree predictions.

XGBoost is a scalable and high-precision implementation of gradient boosting that extends the boundaries of computational power for enhanced tree-like algorithms, mainly designed to improve the productivity of machine learning models and computation speed. With XGBoost, trees are built in parallel, adhering to a level-wise strategy, scanning gradient values, and using these partial sums to evaluate the splitting quality at each possible split in the training set.

Modeling with XGBoost begins with model training, which was conducted based on 86% of the input data. Mean absolute error and mean squared error functions were used to evaluate the model's adequacy.

The mean_absolute_error function calculates the average absolute error, a risk metric that corresponds to the expected value of the absolute error or loss norm.

$$MAE(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} |y_i - \hat{y}_i|, \quad (3)$$

where $\hat{y}_i$ – is the predicting value of i-sample and y_i – is the corresponding truth value.

The mean_squared_error function calculates the mean squared error, a risk metric corresponding to the expected value of the squared error or loss:

$$MSE(y, \hat{y}) = \frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} (y_i - \hat{y}_i)^2, \quad (4)$$

where $\hat{y}_i$ – is the predicting value of i-sample and y_i – is the corresponding truth value.

As a result of constructing a gradient boosting model, the following results were obtained: the MAE and MSE indicators are 0.0560 and 0.0100, respectively. The prediction errors turned out to be quite low, which means that the model adequately predicts the exchange rate of the Ukrainian hryvnia given the specified factors.

The next stage of our research was to determine the importance of the selected factors on the exchange rate of the Ukrainian hryvnia. Figure 10 shows the factor importance indices for the model. As can be seen, the most important factor for the exchange rate of the Ukrainian hryvnia, based on this model, is the level of inflation, specifically the consumer price index for the corresponding month of the previous year (the importance coefficient is close to 0.5). Inflationary processes in the country lead to a decrease in purchasing power and a tendency for the national currency to fall against currencies in countries where inflation is lower. The factor of GDP per capita also has a significant impact: the higher the GDP growth rate, the higher the demand for the national currency and therefore a higher exchange rate. The next factors, whose importance coefficients exceed 0.1, are the unemployment rate and the country's government debt; an increase in these indicators has a negative impact on the national economy and, accordingly, on the exchange rate of the national currency. The volume of gold and foreign exchange reserves also plays a role in determining the exchange rate, if a country does not have sufficient resources to support the exchange rate, it becomes more vulnerable to speculative attacks. Additionally, the factor of international trade to some extent determines the demand for the national currency. The influence of other factors included in this model is somewhat less significant.

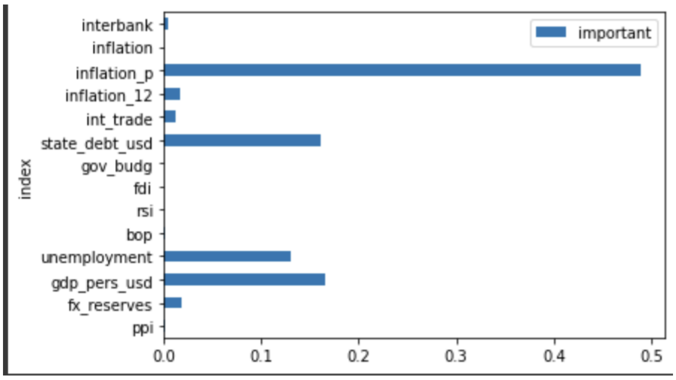

Fig.10. Coefficients of the importance of factors for the model

The final stage of our calculations is to make a forecast for the exchange rate of the Ukrainian hryvnia. Figure 11 shows retrospective forecast values of the exchange rate of the Ukrainian hryvnia for comparison with the real values. The real exchange rate is represented by the blue color on the diagram, while the forecast is represented by the red color.

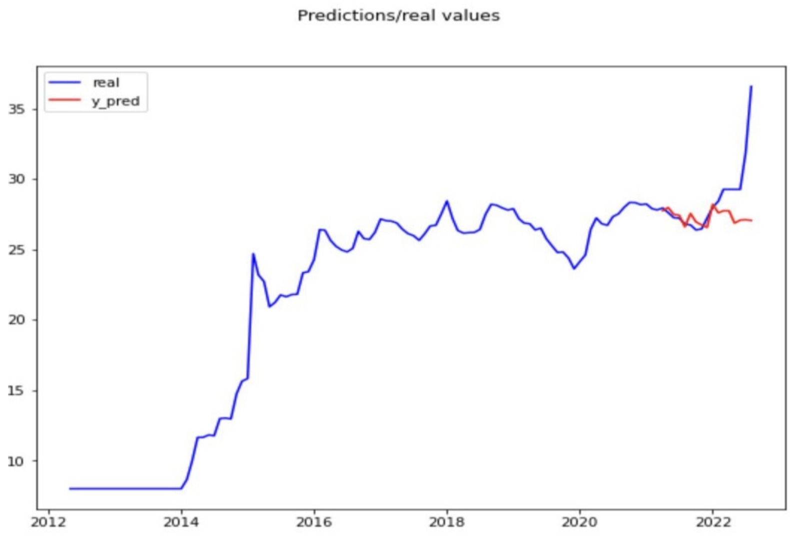

Fig. 11. Chart of the Ukrainian hryvnia exchange rate and retrospective chart of the forecast

Analyzing the chart, we can conclude that in 2021 the retrospective forecast corresponded to the main trends and moved in parallel directions with the real exchange rate, indicating the adequacy of the model. However, in 2022, force majeure factors came to the fore, which cannot be predicted, and even if possible, the impact on the economy of the country and the exchange rate, including the economic-mathematical models used, cannot be estimated. As of the beginning of 2022, the financial and economic indicators of Ukraine did not show negative trends that could have caused an increase in the exchange rate of the Ukrainian hryvnia against the US dollar, but the Russian invasion and the beginning of full-scale war caused a colossal destructive impact on the economy of Ukraine and the national currency exchange rate in particular. Since the model is trained on historical data that did not contain such unprecedented events, or so-called "black swans," the forecast data obtained from our calculations do not correspond to the actual data. At this stage of computer modeling development, it is still difficult to predict such incidents, let alone the impact of such extraordinary events on the economy of the country and the exchange rate of the national currency in particular.

Conclusions

As studies have shown, it is possible to analyze, model, and forecast the exchange rate of a national currency in a country without force majeure circumstances using machine learning methods based on a pre-built multifactor regression dependence of this rate on macroeconomic factors. The results of the retrospective forecast of the Ukrainian hryvnia exchange rate confirmed the high accuracy and effectiveness of the proposed method of forecasting this rate. In 2021, the retrospective forecast corresponded to the main trends and moved in parallel directions with the real rate, indicating the adequacy of the developed model. Under stable political conditions and projected socio-economic development, this model is likely to predict certain fluctuations in the Ukrainian hryvnia exchange rate. The scientific results obtained in the work regarding the proposed approaches to forecasting the national currency exchange rate using machine learning methods should be used in practice by all interested parties, including financial institutions of Ukraine, to achieve stability of the national currency, which in turn will affect the development of the national economy as a whole and the welfare of the population of the country. In the process of further research, the proposed approach to forecasting the country's exchange rate can be improved by adding additional factors that affect this rate to the considered model.

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Vasyl Pryimak **Василь Приймак**	Doctor of Economic Sciences, Professor, Head of Management Information Systems department, Ivan Franko National University of Lviv, Ukraine, e-mail: vasyl.pryymak@lnu.edu.ua https://orcid.org/0000-0003-0244-8661	доктор економічних наук, професор, завідувач кафедри інформаційних систем у менеджменті, Львівський національний університет імені Івана Франка, Львів, Україна
Bohdan Bartkiv **Богдан Бартків**	MSc student of Management Information Systems department, Ivan Franko National University of Lviv, Ukraine, e-mail: bohdan.bartkiv@lnu.edu.ua https://orcid.org/0009-0001-2061-6676	магістрант кафедри інформаційних систем у менеджменті, Львівський національний університет імені Івана Франка, Львів, Україна
Olga Holubnyk **Ольга Голубник**	PhD, Associate Professor of Management Information Systems department, Ivan Franko National University of Lviv, Ukraine, e-mail: olga.holubnyk@lnu.edu.ua https://orcid.org/0000-0003-1211-4614	кандидат економічних наук, доцент кафедри інформаційних систем у менеджменті, Львівський національний університет імені Івана Франка, Львів, Україна