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# SIMULATION OF THE EXCHANGE RATE USING ECONOMIC AND MATHEMATICAL METHODS

*The article is devoted to a comparative analysis of the use of adaptive methods and models, autoregressive models and neural networks in forecasting the exchange rate of the main reserve currencies: the euro, the Swiss franc, the Japanese yen and the British pound against the US dollar. In the course of the research, the works of Ukrainian and foreign scientists on this topic were reviewed and it was determined that the most used methods and models in forecasting the exchange rate based on time series are autoregression models (represented by ARIMA and SARIMA models), neural networks (represented by MLP and ELM architectures) and exponential smoothing methods. In the process of building the models, time series were examined for stationarity based on the Dickey-Fuller test and additive decomposition of the studied time series was performed to determine their main components (trend, seasonality, random component). Construction of forecast models was carried out, on the basis of which their comparative analysis took place. The main shortcomings and problems of using the selected methods are demonstrated and the best predictive models are determined. It is determined that the main drawback of all time series forecasting methods is their "adaptability" to the input data, and the desire to improve the estimation characteristics of the models as a result can lead to the fact that the forecasts differ significantly from the actual values. It was also determined that for forecasting the exchange rate of selected currency pairs, neural networks are best suited, which have both high evaluation characteristics and correspondence of the forecast to real values, and the MLP network shows better results compared to the ELM network. High evaluation characteristics are also demonstrated by adaptive models. However, the linear nature of the forecast does not allow adaptive models to make an accurate forecast in the long term. Although autoregressive models show worse estimation characteristics, they outperform neural networks in terms of matching real values for individual currency pairs.*

***Key words:*** *exchange rate, forecasting, Brown model, Holt model, Holt-Winters model, ARIMA, SARIMA, MLP, ELM, time series decomposition.*

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# МОДЕЛЮВАННЯ ВАЛЮТНОГО КУРСУ ЕКОНОМІКО-МАТЕМАТИЧНИМИ МЕТОДАМИ

*Стаття присвячена порівняльному аналізу використання адаптивних методів та моделей, авторегресійних моделей та нейронних мереж у прогнозуванні курсу основних резервних валют: євро, швейцарського франка, японської єни та британського фунта щодо долара США. У процесі дослідження було розглянуто праці українських та іноземних вчених з наведеної тематики та визначено, що найбільш використовуваними методами й моделями у прогнозуванні курсу валют на основі часових рядів є авторегресійні моделі (представлені ARIMA та SARIMA моделями), нейронні мережі (представленні MLP та ELM архітектурами) та методи експоненційного згладжування. У процесі побудови моделей проведено дослідження часових рядів на стаціонарність на основі тесту Дікі-Фуллера та* *здійснено адитивну декомпозицію досліджуваних часових рядів для визначення основних їх складових (тренд, сезонність, випадкова складова). Здійснено побудову прогнозних моделей, на основі яких відбувся їх порівняльний аналіз. Продемонстровано основні недоліки та проблеми використання обраних методів та визначено кращі прогнозні моделі. Визначено, що основним недоліком усіх методів прогнозування на основі часових рядів є їх «пристосовуваність» до вхідних даних, а прагнення покращити оціночні характеристики моделей в результаті може призвести до того, що прогнози значним чином відрізнятимуться від фактичних значень. Також визначено, що для прогнозування курсу обраних валютних пар найкраще підходять нейронні мережі, які мають як високі оціночні характеристики, так і відповідність прогнозу реальним значенням, причому кращі результати демонструє MLP мережа у порівнянні з ELM мережею. Високі оціночні характеристики також демонструють адаптивні моделі. Проте, лінійних характер прогнозу не дає змоги адаптивним моделям здійснити точний прогноз у довгостроковій перспективні. Авторегресійні моделі хоча і демонструють гірші оціночні характеристики, проте в розрізі відповідності реальним значенням вони за окремими валютними парами перевершують нейронні мережі.*

***Ключові слова:*** *курс валют, прогнозування, модель Брауна, модель Хольта, модель Хольта-Вінтерса, ARIMA, SARIMA, MLP, ELM, декомпозиція часового ряду.*

**Introduction.** The exchange rate is one of the main macroeconomic indicators. There are no closed countries in the world, they somehow interact with other countries and participate in international trade. For this purpose, currencies of other countries are used. To carry out effective foreign economic activity for various business entities, there is a need to take into account the behaviour of one or another currency. That is why the exchange rate is interesting from the point of view of predicting its possible change. This especially applies to forecasting changes in the exchange rate of the national currency, as the latter is an important aspect of planning the income and expenditure part of the budget. Also, the monetary policy of the state is built on the basis of a possible change in the exchange rate, on which the well-being of ordinary citizens of the country depends. Forecasting exchange rates is also interesting for enterprises, especially for those that are engaged in export or import activities and are forced to take into account currency risks in the cost of their own products.

Various methods and models are used to forecast the exchange rate. They are presented in the form of autoregressive models, exponential smoothing methods, neural networks, etc. Moreover, all these methods are actively developed and modified to solve this or that problem. Therefore, there is a need to carry out a comparative analysis of the most used methods and models used to forecast the exchange rate.

**Analysis of recent research and publications.** Numerous works of Ukrainian and foreign researchers are devoted to the issue of currency exchange rate forecasting. In particular, Amat K., Tomas M., Gilles S. [1] described in their work the basics and possibilities of using machine learning methods for forecasting the exchange rate, Al-Gounmein, R. S., Ismail, M. T. [2] demonstrated the peculiarities of forecasting exchange rate based on the Box-Jenkins ARIMA model, R.Adhikari and R.Agrawal [3] paid attention to the forecasting of time series based on artificial neural networks. Chen Y. and G. Zhang considered the issue of currency rate forecasting based on genetic algorithms [4]. Beckmann, J., and R. Schüssler [5] in their work described the forecasting of the exchange rate in conditions of uncertainty of parameters and models. Tatar M.S. and O.A. Sergiyenko investigated the issue of forecasting the exchange rate in the system of managing the competitiveness of enterprises [6]. Despite the thorough research conducted by various scientists, the comparative calculation of the exchange rate forecast by various methods to determine the most acceptable remains an important task.

**The purpose and tasks of the research.** The purpose of the study is to carry out a comparative analysis of the most used methods and models of forecasting the exchange rate based on time series of the main reserve currencies: the euro, the Swiss franc, the Japanese yen, the British pound and the US dollar.

**Presentation of basic material.** When researching articles on the Kaggle platform (an analytics and predictive modelling competition platform where statisticians and data miners compete to create the best models for forecasting and describing data provided by companies or users) [7] for the query "forecast exchange rate" in 41% of articles used autoregressive models for forecasting the exchange rate, 10% of articles used exponential smoothing methods, and 17% of articles used neural networks. Moreover, among the autoregressive models, the most used are the ARAIMA and SARIMA models, which account for the majority of research. Among neural networks, the ordinary multilayer perceptron MLP and the extreme learning machine ELM are particularly popular. As for exponential smoothing methods, they are represented by a wide range of models: Holt model, Winters model, Holt-Winters model, Theil-Wage model, Brown model, Harrison model, Trigg method, Trigg-Leach method, Chow model, harmonic weight method, etc [8]. However, the most widely used among them are Brown's method (as the easiest to implement method of this class of models), Holt's method (due to the possibility of taking into account the trend component) and its modification – the Holt-Winters method, which is able to take into account both trend and seasonal components. Therefore, it is on the basis of these methods and models that the construction of predictive models and their comparative analysis will be carried out. To implement these methods, the R programming language environment and the tools available in it were used. Data on the exchange rates of the euro, Swiss franc, Japanese yen and British pound against the US dollar were used to build models and make forecasts. The period of data taken for research is 5 years from December 01, 2016 to November 01, 2022, the frequency of observations is monthly. Also, before starting the research, the samples were divided into two. The first is a training one, based on which models will be built, the number of elements of this sample is equal to length(data)-h(forecast period), that is, from the total number of observations, we chose a series without the last h observations, in our case, the forecasting period is 6 months. Based on the remaining values, the quality of the forecast will be checked, namely the assessment of the ability of the models to make predictions that really correspond to the real phenomenon. This necessity is caused by the fact that most methods and models of forecasting based on time series "fit" to the data, and therefore the estimated characteristics indicate only the descriptive properties of the models, and not the ability to give accurate forecasts that correspond to real values. The EUR/USD currency pair will be used to demonstrate the construction process. Thus, before starting the construction of predictive models, the time series was checked for stationarity using the Dickey-Fuller test (Fig. 1)

```
        Augmented Dickey-Fuller Test

data:  output
Dickey-Fuller = -2.0968, Lag order = 4, p-value = 0.5359
alternative hypothesis: stationary
```

**Fig. 1. Dickey-Fuller test for stationarity of the EUR/USD exchange rate**

The obtained p-value of 0.5359 (>0.05) indicates that the structures present in the time series are time-dependent, that is, the time series is non-stationary [9]. This is evidenced by the additive decomposition of the time series of the exchange rate of the EUR/USD currency pair (Fig. 2).

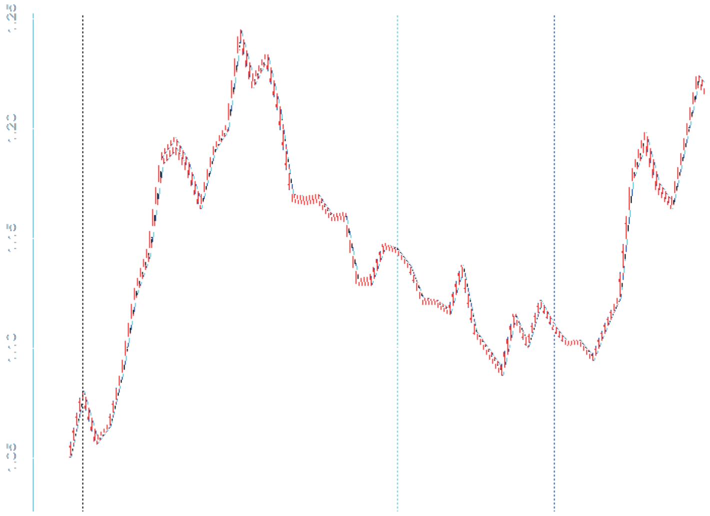


**Fig. 2. Graph of the additive decomposition of the time series of the exchange rate of the EUR/USD currency pair**

Fig. 2 shows that the basis of the time series is a clearly defined trend component. We can also observe a clearly expressed seasonal component, which is presented in the form of fluctuations with a periodicity of 12 months. However, the seasonal component is insignificant, and its contribution is minimal. This behaviour of time series is characteristic of all studied currency pairs. First, this is because all currency pairs are taken in relation to the US dollar. Secondly, the reason for the uniformity of behaviour is that the selected currencies represent countries (groups of countries) that have close economic relations (Switzerland, Great Britain, the European Union, Japan). Also, these countries have the same business calendar, and therefore the presented seasonal component is almost identical in all currency pairs. A clear increase is observed during the New Year holidays and during the summer holidays. Checking the time series for the presence of various components was necessary for the further process of modelling adaptive models (Holt and Holt-Winters, for which the presence of a trend and seasonal component is an important fact) and autoregressive models, which work effectively only with stationary series. Therefore, for our data, we will need to run the time series difference operator d. The same problem is inherent in selected architectures of neural networks, which need to be informed about the presence of various components in the time series in the form of parameters.

To build models and forecast based on ARIMA and SARIMA methods, the forecast library of the R environment was used. Adaptive methods were implemented using software code based on their mathematical description. The nnfor software library [11] was chosen as a tool for building neural networks. The search for smoothing parameters of adaptive methods and models was carried out by minimizing the root mean square error. However, one should be careful here, since the studied methods seek to minimize it by maximizing the smoothing coefficient of the time series and minimizing the smoothing coefficients of the trend and seasonal components. Therefore, it is necessary to set additional restrictions for each individual time series. The search for the parameters of autoregression models was carried out by selecting the order of models for which the index of autocorrelation and partial autocorrelation between the residual levels of the series was within the specified limits. As for the selection of parameters of neural networks, as in the case of adaptive methods and models, they were selected by minimizing the root mean square error. However, as with adaptive models, care must be taken as the network can have a high quality of description, which is achieved by increasing the number of hidden layer nodes. As a result, this leads to a deformation of the forecast. Such a situation vividly demonstrates the effect of "overtraining" of the network. Therefore, there is a need to check the received forecasts on real values. After preparing the data and finding the appropriate parameters of the models, we will move on to the evaluation of the construction results. Graphic visualization of the built Brown model is presented in Fig. 3.

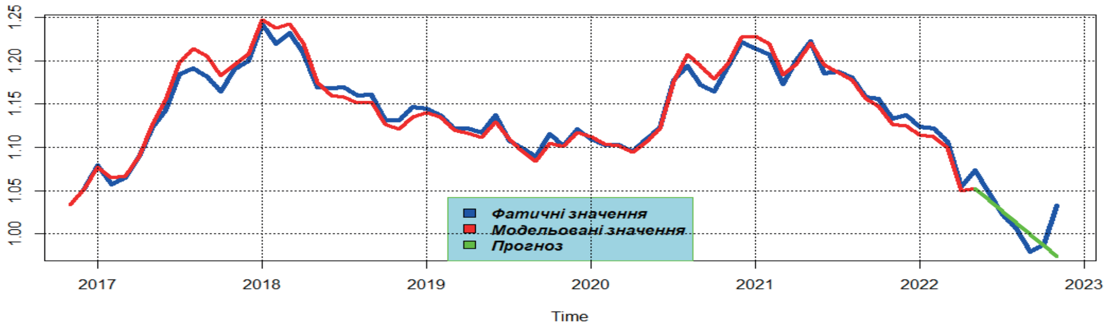



**Fig. 3. Results of building the Brown model based on the EUR/USD exchange rate**

As we can see on the graph, the model describes the investigated time series quite well. However, it reacts somewhat poorly to sharp price fluctuations present in the time series. As for the forecast, the longer the forecasting period, the greater the deviation of the forecasted values from the real ones. In addition, the model is not able to take into account the change in the trend, which is the main drawback of this class of models. The forecast has a linear character, and therefore becomes ineffective when structural shifts in the phenomenon appear. In general, in the short term (up to 3 months), the model gives a good forecast of this phenomenon, further increasing the forecast period is ineffective.

The results of calculations based on the Holt model with smoothing coefficients of the series levels of 0.71 and the trend of 0.42 are presented in Fig. 4.

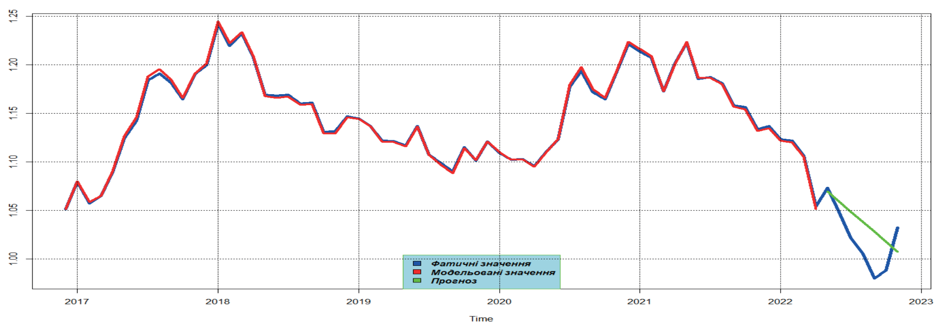



**Fig. 4. Results of calculations according to the Holt model based on the EUR/USD exchange rate**

The obtained results show that the Holt model describes the phenomenon better than the Brown model, because it can take into account the trend component. However, like in Brown's model, the forecast is linear. As for the forecasting period, the model is effective only for a short period of time and loses its effectiveness when the trend changes. We can also observe that the model reacted sharply to the last fluctuation, which led to the fact that the forecast was overestimated compared to the actual values. This is one of the main disadvantages of adaptive methods and models, which are given the most attention to the last observation and make it based on further forecast. If there is a fluctuation in the last observed, then this will lead to a bias in the forecasts. Similar behaviour is demonstrated by the Holt-Winters model with smoothing parameters a=0.61, b=0.59, s=0.15, where a, b, s are the smoothing parameters of the levels of the series, trend, and seasonal component in accordance. The seasonality period is 12 months. The construction results are presented in Fig. 5.

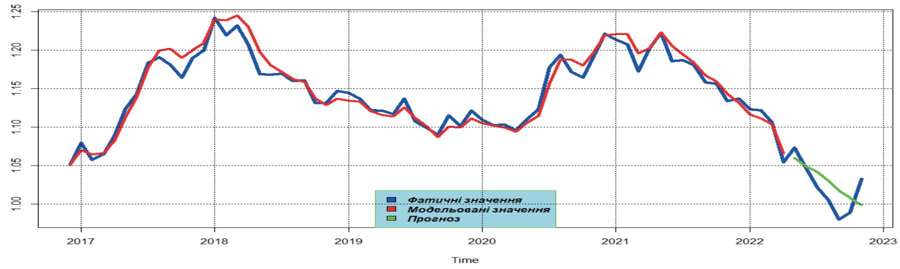
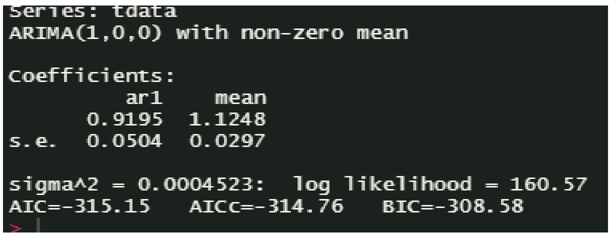



**Fig. 5. Results of building the Holt-Winters model based on the EUR/USD exchange rate**

The Holt-Winters model (Fig.5) quite accurately describes the phenomenon. However, unlike the Holt model, the influence of the last observation is not so critical, but, like other adaptive methods and models, the Holt-Winters model is not able to predict the possible fast variable of the phenomenon, which leads to an overestimation of the predicted values compared to the actual ones.

Autoregressive models can only work with stationary series. If the time series are non-stationary, then the non-stationary time series is reduced to a stationary one using the difference parameter. The "forecast" library function was used to build an autoregressive ARIMA model, which builds a model with parameters that satisfy optimality conditions. This is usually the model with the lowest AIC. Each individual model is tested in turn until the information criterion decreases. If the information criterion increases in the next step, the function stops the search. The model characteristics are shown in Fig. 6.



```
Series: tdata
ARIMA(1,0,0) with non-zero mean

Coefficients:
         ar1    mean
      0.9195  1.1248
s.e.  0.0504  0.0297

sigma^2 = 0.0004523:  log likelihood = 160.57
AIC=-315.15   AICc=-314.76   BIC=-308.58
>
```

**Fig. 6. Parameters of the EUR/USD time series ARIMA(1,0,0) model built using the "auto.arima" function**

As we can see, the function built a normal autoregressive model of the form AR(1). Although the AIS parameter is quite low, one should check for autocorrelation and partial autocorrelation between the residuals of the series. To do this, you should use the "tsdisplay" function, which will make it possible to estimate both the magnitude of the error of the built model and the presence of a relationship between the residual levels of the series.

As we can see on the graph on the 11th-12th log, the partial autocorrelation function exceeds the allowed limits. This indicates that the parameters (orders of the autoregressive function and the moving average) of the model should be searched in the range from 1 to 12. This can be achieved by sorting or using an optimization function. Lags should be added to the model until the autocorrelation between residuals disappears. Also, do not forget that the EUR/USD series is non-stationary, so you need to add a time series difference operator. To build a new ARIMA model you should use the "arima" function.

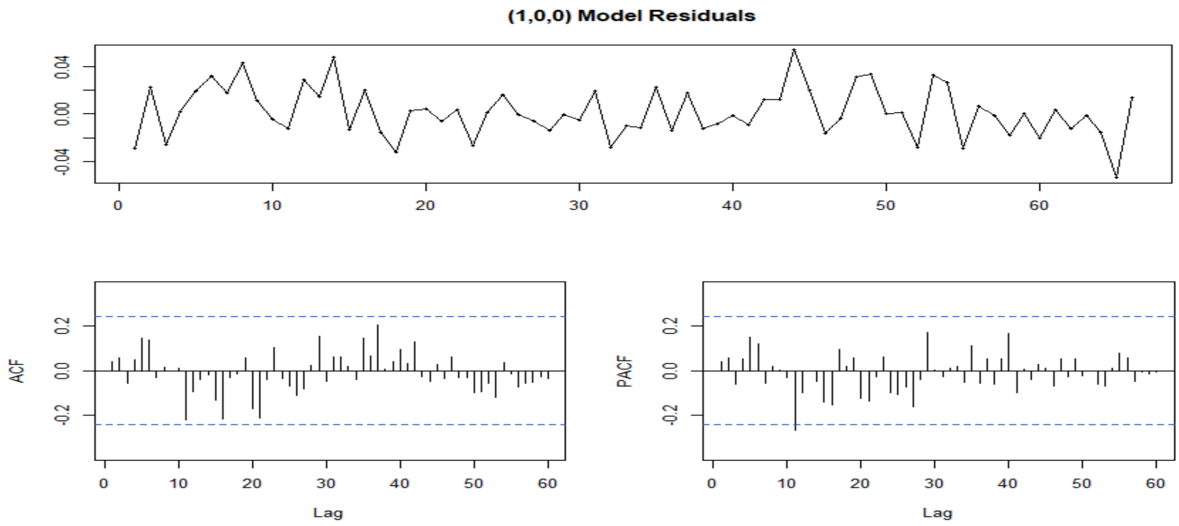



**Fig. 7. Graphs of the residuals of the ARIMA(1,0,0) model of the EUR/USD currency pair and the presence of autocorrelation or partial autocorrelation between them**

It needs to input a time series and a vector of parameters (orders of autoregression and moving average, as well as the order of the difference in the levels of the series). It was determined that the best way to describe the behaviour of the EUR/USD time series is the ARIMA(2,2,2) model (Fig. 8).

```
Call:
arima(x = tdata, order = c(2, 2, 2))

Coefficients:
         ar1      ar2      ma1     ma2
      0.7859  -0.326  -1.7772  1.0000
s.e.  0.1203   0.126   0.0932  0.1031

sigma^2 estimated as 0.0004105:  log likelihood = 155.49,  aic = -300.98
```

**Fig. 8. Parameters of the EUR/USD time series ARIMA(2,2,2) model**

Fig. 8 shows the obtained parameters of the model, which are used further to construct forecast values. AIC rose slightly, but only marginally. As for autocorrelation and partial autocorrelation, Fig. 9 we can see that it is within acceptable limits.

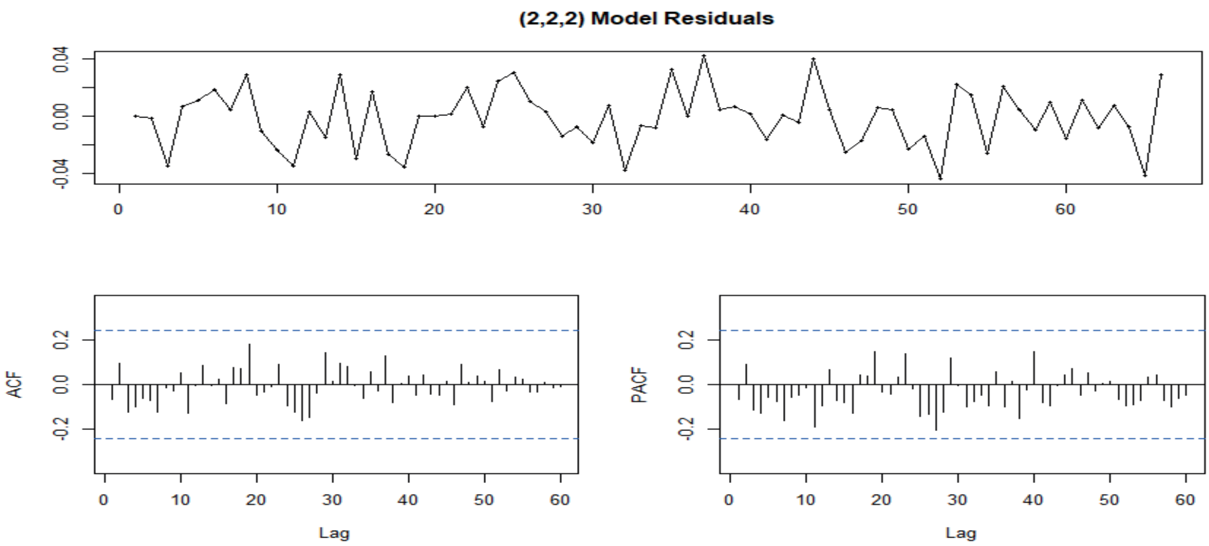



**Fig. 9. Graphs of the residuals of the ARIMA(2,2,2) model of the EUR/USD currency pair and the presence of autocorrelation or partial autocorrelation between them**

The results of the built model, presented in fig. 10, quite accurately describe the incoming time series of the EUR/USD exchange rate. We can also observe that the predicted values fully correspond to the actual values. The high accuracy of forecasts of ARIMA and SARIMA models leads to their use for forecasting various phenomena based on time series (on the Kaggle platform, 15% of all articles on the "forecast" request are devoted to these models).

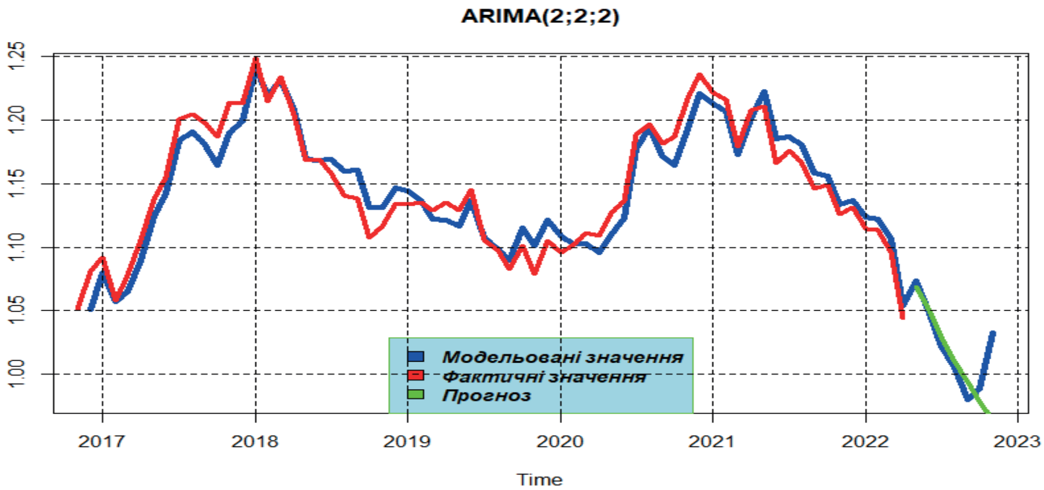



**Fig. 10. Results of building the ARIMA(2,2,2) time series model of the EUR/USD currency pair**

At the stage of testing the data for stationarity using the additive decomposition of the time series, a slight seasonal component was detected in the time series of the EUR/USD currency pair. This necessitates the construction of the SARIMA model. In fig. 10 we can see the simulation results. The SARIMA(0,1,2)X(0,1,1) model was the best variant of the model taking into account seasonality.

```
Call:
arima(x = tdata, order = c(0, 1, 2), seasonal = c(0, 1, 1))

Coefficients:
          ma1      ma2     sma1
      -0.3144  -0.2189  -0.6545
s.e.   0.4385   0.1739   0.4269

sigma^2 estimated as 0.0004675:  log likelihood = 153.79,  aic = -299.59
```

**Fig. 10. Parameters of the EUR/USD time series SARIMA(0,1,2)X(0,1,1) model**

The AIS value is slightly higher than the ARIMA model. Autocorrelations of residuals are within normal limits (Fig. 11).

The SARIMA model (Fig. 12) describes the time series of the EUR/USD currency pair in a similar way to the ARIMA model, but we can observe a slightly delayed reaction to a change in trend or fluctuations at the points of local extremes. However, unlike the ARIMA model, the SARIMA model provided a much worse forecast compared to the actual values.

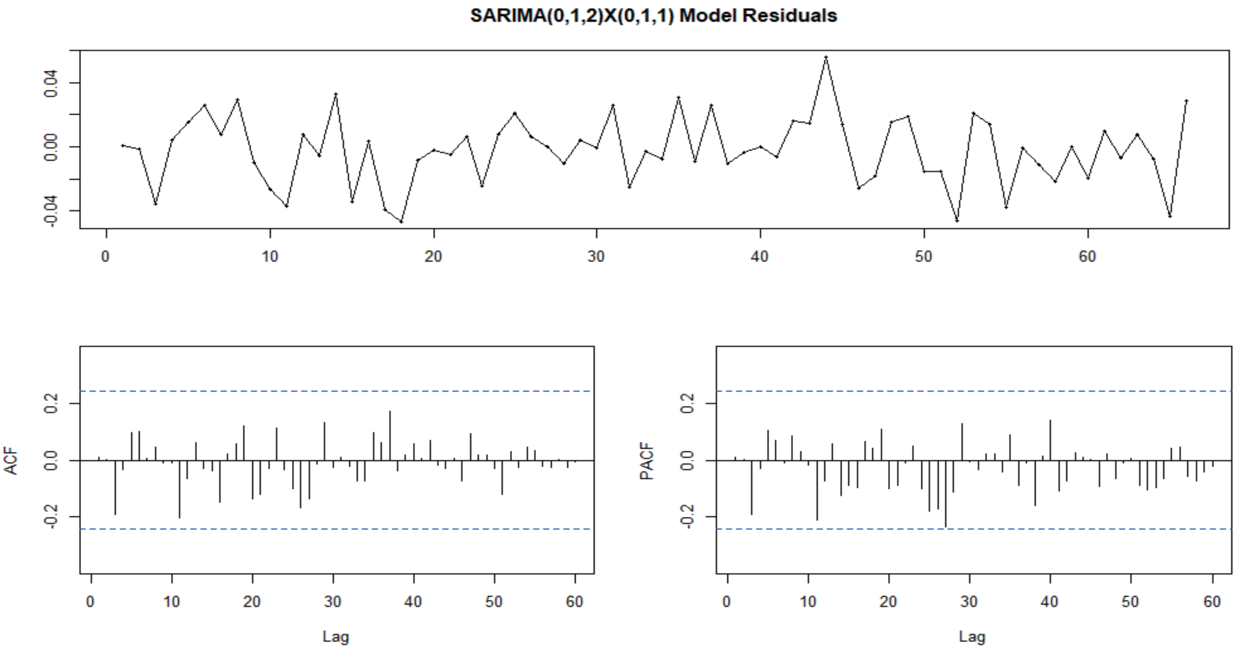



**Fig. 11. Graphs of the residuals of the SARIMA(0,1,2)X(0,1,1) model of the EUR/USD currency pair and the presence of autocorrelation or partial autocorrelation between them**

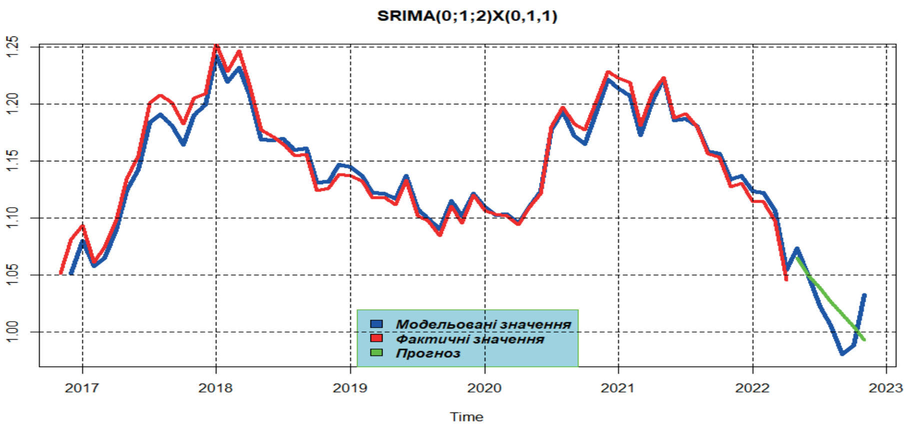



**Fig. 12. Results of constructing the SARIMA(0,1,2)X(0,1,1) time series model of the EUR/USD currency pair**

Neural networks are a modern tool for the study of various phenomena. MLP, ELM architecture of neural networks is chosen as one of the most popular for currency rate forecasting. Both are implemented in the "nnfor" library of the R programming language. This library allows you to set various parameters of networks, which greatly facilitates their construction. First, an MLP network was built with parameters: number of lags 1:12, time series level difference parameter from 1 to 6, maximum number of hidden layer nodes 10. As a result, an MLP neural network was built with 3 input nodes, 4 hidden layer nodes and one node source layer. This is a fairly simple neural network architecture. However, she quite accurately described the input time series (Fig. 13).

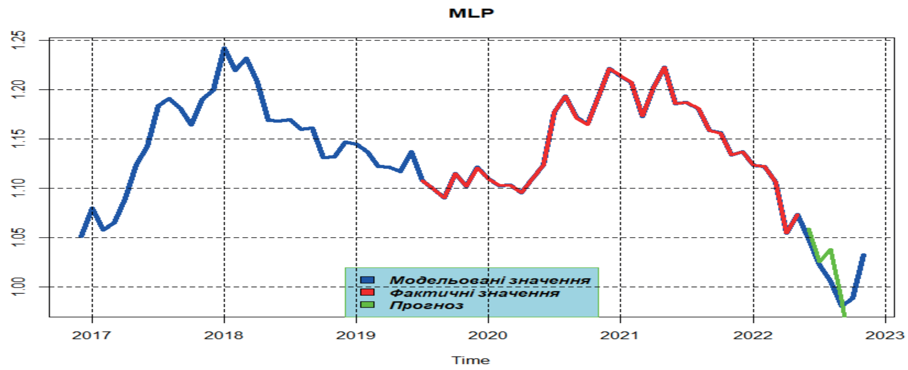



**Fig. 13. Results of MLP construction of the EUR/USD exchange rate prediction network**

The neural network fully adapted to the data, resulting in a partial distortion of the forecast. The network sought to account for as many fluctuations as possible and took the last fluctuation into account in the forecast. In general, the model provided a fairly accurate forecast, especially for the first two periods.

To build the ELM network, the following parameters were set: the number of lags will be determined automatically, the time series level difference parameter from 1 to 3, the number of nodes of the hidden time series is 25. The graphic display of the constructed network is presented in Fig. 14.

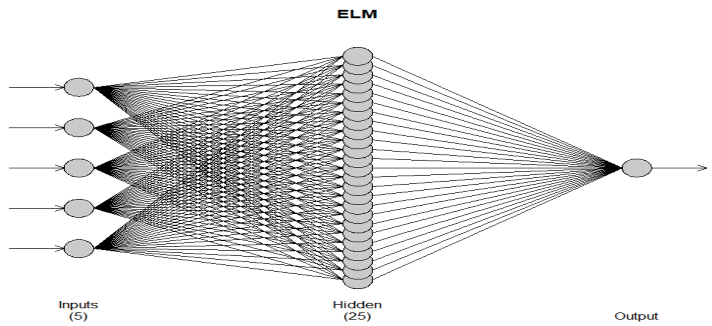



**Fig. 14. Graph of the ELM neural network for forecasting the currency exchange rate of the EUR/USD currency pair**

Compared to the MLP network, the ELM network has a much larger number of hidden layer nodes, while the speed of construction in the ELM network is much higher. By increasing the number of nodes of the hidden layer, it is possible to significantly increase the accuracy of the description of the input time series. However, this will only lead to the fact that the neural network will try to take into account the maximum number of fluctuations in the forecast, which will lead to its significant deformation.

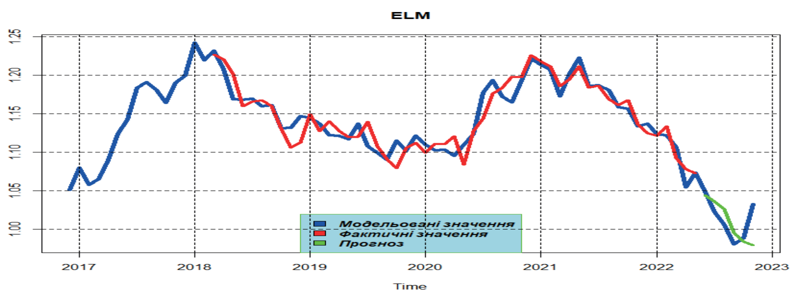



**Fig. 15. The results of the construction of the ELM network for forecasting the exchange rate of the EUR/USD currency pair**

On Fig. 15 we can observe that the ELM network describes the phenomenon much worse than the MLP network. The same situation applies to the implemented forecast, which was deformed due to a significant number of fluctuations. So, we can say that the ELM neural network is quite sensitive to the fluctuations present in the time series and tries to transfer them to the forecast.

In addition to forecasting models for the euro/dollar currency pair, models were also built for forecasting the exchange rate of the Swiss franc, Japanese yen, and British pound against the US dollar. They demonstrated a similar situation. The only difference was that different model parameters were specified.

The comparative analysis of the built models was carried out on the basis of the coefficient of determination, the average absolute error of the forecast and the average absolute error. Among the adaptive methods and models, the best results for all currency pairs were demonstrated by the Holt model (table 1).

*Table 1*

**Assessment characteristics of the accuracy of adaptive models**

| Model | Characteristics/Currency pair | R^2 | MAPE | MAE |
|---|---|---|---|---|
| Brown | EUR/USD | 0,96 | 0,66 | 0,007 |
| | CHF/USD | 0,93 | 0,73 | 0,008 |
| | JPY/USD | 0,94 | 0,71 | 0,006 |
| | GBP/USD | 0,94 | 0,74 | 0,009 |
| Holt | EUR/USD | 0,99 | 0,12 | 0,0014 |
| | CHF/USD | 0,99 | 0,024 | 0,003 |
| | JPY/USD | 0,99 | 0,0019 | 0,00017 |
| | GBP/USD | 0,99 | 0,01 | 0,00015 |
| Holt-Winters | EUR/USD | 0,95 | 0,72 | 0,008 |
| | CHF/USD | 0,97 | 0,51 | 0,0054 |
| | JPY/USD | 0,95 | 0,67 | 0,006 |
| | GBP/USD | 0,97 | 0,55 | 0,007 |

The reason for this is that the basis of the time series is the trend component. This is effective for forecasting based on short time series for a period of no more than 1-2 periods, as demonstrated by adaptive models using the example of the EUR/USD currency pair. Further increases in the forecast period are ineffective.

For autoregressive models the best results were demonstrated by the SARIMA model for most currency pairs, except for the CHF/USD currency pair (Table 2). This indicates the presence of a seasonal component that has a corresponding influence on the phenomenon.

*Table 2*

**Estimated accuracy characteristics of autoregressive models**

| Model | Characteristics/Currency pair | R^2 | MAPE | MAE |
|---|---|---|---|---|
| ARIMA | EUR/USD | 0,92 | 1 | 0,014 |
| | CHF/USD | 0,93 | 0,75 | 0,007 |
| | JPY/USD | 0,92 | 0,63 | 0,005 |
| | GBP/USD | 0,94 | 0,71 | 0,009 |
| SARIMA | EUR/USD | 0,96 | 0,64 | 0,007 |
| | CHF/USD | 0,92 | 0,87 | 0,009 |
| | JPY/USD | 0,96 | 0,51 | 0,004 |
| | GBP/USD | 0,96 | 0,91 | 0,01 |

In general, the estimated characteristics of the models are close to each other. Also, the autoregressive models demonstrate a high correspondence of the predicted values with the actual values from the test sample.

Among neural networks, the undisputed leader is the MLP network (Table 3). But it is quite difficult to implement it on a large sample, as it requires significant computing resources. The ELM network builds networks quite quickly.

There are situations when the speed of obtaining a forecast is more determining factor than its accuracy. Therefore, the choice of network depends on the needs of the researcher. Both networks demonstrate a high correspondence between the predicted values and the actual ones from the test sample for most currency pairs.

*Table 3*

**Evaluation characteristics of the accuracy of neural networks**

| Model | Characteristics/Currency pair | R^2 | MAPE | MAE |
|---|---|---|---|---|
| MLP | EUR/USD | 0,99 | 0,01 | 0,001 |
| | CHF/USD | 0,99 | 0,1 | 0,001 |
| | JPY/USD | 0,99 | 0,019 | 0,002 |
| | GBP/USD | 0,98 | 0,52 | 0,007 |
| ELM | EUR/USD | 0,94 | 1,04 | 0,012 |
| | CHF/USD | 0,95 | 0,73 | 0,007 |
| | JPY/USD | 0,94 | 0,75 | 0,007 |
| | GBP/USD | 0,97 | 0,76 | 0,009 |

*Table 4*

**Comparative analysis and assessment of the accuracy of the Holt model, MLP network, ARIMA and SARIMA models**

| Model | Characteristics/Currency pair | R^2 | MAPE | MAE |
|---|---|---|---|---|
| Хольта | EUR/USD | 0,99 | 0,12 | 0,001 |
| | CHF/USD | 0,99 | 0,024 | 0,003 |
| | JPY/USD | 0,99 | 0,0019 | 0,0001 |
| | GBP/USD | 0,99 | 0,01 | 0,00015 |
| MLP | EUR/USD | 0,99 | 0,01 | 0,001 |
| | CHF/USD | 0,99 | 0,1 | 0,001 |
| | JPY/USD | 0,99 | 0,019 | 0,002 |
| | GBP/USD | 0,98 | 0,52 | 0,007 |
| SARIMA | JPY/USD | 0,96 | 0,51 | 0,004 |
| | GBP/USD | 0,96 | 0,91 | 0,01 |
| | EUR/USD | 0,96 | 0,64 | 0,007 |
| ARIMA | CHF/USD | 0,93 | 0,75 | 0,007 |

Table 4 shows that the Holt model and the MLP network have the best results for assessing the accuracy of forecast models. The Holt model better describes the behaviour of the Japanese yen and British pound currency pairs against the US dollar. At the same time, the MLP network carries out a better description of the currency pairs of the euro and the Swiss franc against the US dollar. In comparison with them, autoregressive models show slightly worse evaluation characteristics of model accuracy.

As we could see on the example of modelling and forecasting the behaviour of the currency pair EUT/USD, the ARIMA model was the best able to predict the behaviour of the phenomenon in the future. A similar situation is inherent in other currency pairs, where autoregressive models and neural networks demonstrate the best correspondence between forecast values and actual ones from the test sample. Based on this, we can conclude that the evaluation characteristics of the accuracy of forecasts when building models based on time series are measures of the accuracy of the description of the model of the input time series ("adaptability to the data"). Therefore, when forecasting on the basis of time series not always should rely exclusively on the estimated characteristics of the accuracy of the model. The forecasts should be check for compliance with their real values.

**Conclusions.** Adaptive networks, autoregressive models and neural networks demonstrate high evaluation characteristics of the accuracy of predictive models. According to the results of the research, the input time series of MLP are best described by the neural network and the Holt model. However, the correspondence of the predicted values with the actual ones shows that autoregressive models, namely the ARIMA model and neural networks, show better results. Therefore, in the process of building and implementing a forecast based on the above-mentioned models, one should not rely exclusively on the evaluation characteristics of the accuracy of the model. It was also established that although different currency pairs show similar behaviour over time, different models show better results for individual currency pairs. Modelling shows that each currency pair should be considered as a separate phenomenon and methods of assessment and forecasting should be selected separately for each currency pair.

**References:**

1. Amat, C., Tomasz, M., & Gilles, S. (2018). Fundamentals and exchange rate forecast ability with machine learning methods. Journal of International Money Finance, vol. 88, pp. 1-24.

2. Al-Gounmein, R. S., & Ismail, M. T. (2020). Forecasting the exchange rate of the Jordanian Dinar versus the US dollar using a Box-Jenkins seasonal ARIMA Model. International Journal of Mathematics and Computer Science, vol. 15(1), pp. 27-40.

3. Adhikari, R., and R. K. Agrawal. (2014). A Combination of Artificial Neural Network and Random Walk Models for Financial Time Series Forecasting. Neural Computing & Applications, vol. 24 (6), pp. 1441–9.

4. Chen, Y., and G. Zhang. (2013). Exchange Rates Determination Based on Genetic Algorithms Using Mendel's Principles: Investigation and Estimation under Uncertainty. Information Fusion, vol. 14 (3), pp. 327–33.

5. Beckmann, J., and R. Schüssler. (2016). Forecasting Exchange Rates under Parameter and Model Uncertainty. Journal of International Money and Finance, vol. 60 (February), pp. 267–88.

6. Sergienko O., Tatar M. (2013) Exchange rate forecasting models in the enterprise competitiveness management system. Problems of the Economy.Vol.. 2. pp. 268–278.

7. Kaggle. Kaggle: Your Machine Learning and Data Science Community. URL: https://www.kaggle.com/ (date of access: 08.11.2022).

8. Melnyk O., Novoseletskyy O. (2022). Economic and mathematical tools for predicting the currency exchange rate. Scientific opinion: Economics and Management. URL: https://doi.org/10.32836/2521-666x/2022-78-24 (date of access: 05.11.2022).

9. Augmented dickey-fuller test in R | r-bloggers. R-bloggers. URL: https://www.r-bloggers.com/2022/06/augmented-dickey-fuller-test-in-r/ (date of access: 26.11.2022).

10. Forecast package – RDocumentation. Home – RDocumentation. URL: https://www.rdocumentation.org/packages/forecast/versions/8.14 (date of access: 07.11.2022).

11. Kourentzes N. Tutorial for the nnfor R package. Main Redirection to ssl. URL: https://kourentzes.com/forecasting/2019/01/16/tutorial-for-the-nnfor-r-package/ (date of access: 03.12.2022).