# Forecasting the foreign exchange market using the modified G (ARCH) model

Nikita Sviatov
*Samara National Research University*
Samara, Russia
nikitasviatov@gmail.com

Alexander Blagov
*Samara National Research University*
Samara, Russia
alexander.blagov@gmail.com

***Abstract*—The article provides a comparative analysis of existing models for forecasting prices in the foreign exchange market. The authors propose an improved modification of the model that is most suitable for predicting the behaviour of the EUR / USD currency pair. The calculation is performed by the developed software tool that processes and analyses the entered parameters of the time series.**

***Keywords—data analysis, time series analysis, auto-regression, foreign exchange market***

## I. Introduction

Currently, there is great interest in the stock market, and in particular in the foreign exchange market. Many researchers create algorithms and methods for its prediction [1-4]. Therefore, it is of great interest to analyze existing approaches, as well as develop a model that has a number of advantages over existing analogs. Given the increased volume of data necessary for analysis, new, often non-classical approaches are required. These include problem solving using artificial intelligence. Currently, it is used in various fields of activity, including the financial sector. The authors set the task of finding the model most suitable for predicting the behavior of the EUR / USD currency pair, as well as its improvement.

Many authors conducted research on this topic and they got different results. For example, an interesting approach is described in the article on fractal time series analysis [1].

A number of articles describe works on expert short-term forecasting of the foreign exchange market [2-4]. The paper [3] presents research on the fundamental analysis of world currency markets. The article [5] describes the campaigns used in predicting changes in time series parameters.

## II. Analysis of Existing Models

Consider the currently most popular models for forecasting prices in the foreign exchange market. The model of autoregression is moving average (ARMA) is one of the mathematical models used to analyze the forecasting of stationary time series in statistics. The ARMA model generalizes two simpler time series models: the autoregressive (AR) model and the moving average (MA) model [4]. As a rule, ARMA models, although they have a more complex structure, in comparison with AR and MA models, are characterized by fewer parameters. ARMA models also have a number of other properties that determine their practical attractiveness [6].

The predicted value is determined as the following linear function (1)

$$Y_t = c + e_t + \beta e_{t-1} + u_t, \qquad (1)$$

where $e_t$ is deviation of the actual value from the forecast in the previous period, $\beta$ is coefficient before $e_t$, $u_t$ is "White noise" is residues that do not correlate with the remnants of the previous period, $c$ is constant.

Another well-known model is the autoregressive model of conditional heteroskedasticity - (G) ARCH. The meaning of this model is encrypted in its name. So, the ARCH model uses past values of the series for forecasting (autoregression), which in turn is heterogeneous, which is manifested in the variability of the variance of random error (heteroskedasticity) [7] [8]. This model was proposed by Robert Engle in 1982 [9], it can be represented as the following equation (2):

$$\sigma_t^2 = \alpha_0 + \alpha_1 r_{t-1}^2 + \cdots + \alpha_i r_{t-1}^2, \qquad (2)$$

where $\sigma_t$ is volatility function, m$\alpha_t$ is base volatility, $r_{t-1}^2$ is squares of past asset returns, $\alpha_i$is model coefficients showing the effect of past asset returns on the current value of volatility.

The (G) ARCH model has a number of disadvantages, for example, the need to choose a large order of the model so that the results are better [10-11].

Let's try to compare the effectiveness of the ARMA and G (ARCH) models[12-14] on the EUR / USD currency pair (Figure 1).

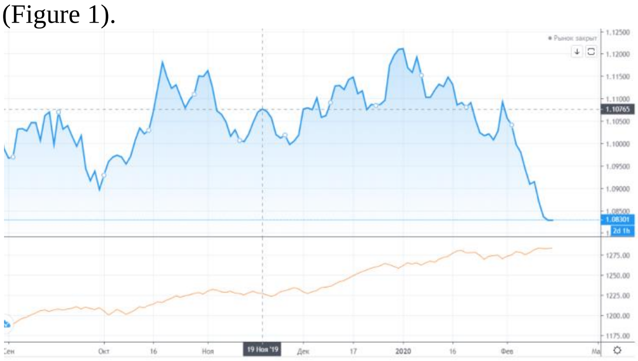

Fig. 1. The graph of the behavior of a currency pair over a time interval with a highlight of the start date of the study.

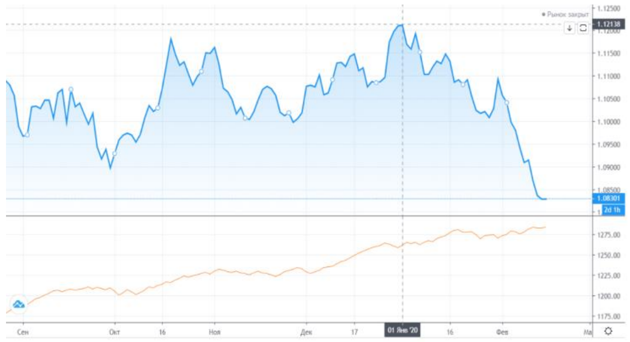

Fig.2. The graph of the behavior of a currency pair over a time interval with the highlighting of the end date of the study.

At the beginning of the study period on November 19, 2019, the currency pair was at around 1.08301. At the end of this period, 1.2138 (Figure 2).

For this study period, a forecast was made using both ARMA and G (ARCH) models. Table 1 shows the results of these models.

TABLE I. THE RESULTS OF THE MODELS ARMA AND G (ARCH) FOR 42 DAYS

| Parameters | ARMA Model | Model G (ARCH) |
|---|---|---|
| Mean | 0.0000209 | 0.0000299 |
| Standard error | 0.0000427 | 0.0000402 |
| Standard deviation | 0.0005642 | 0.0005222 |
| Scope | 0.0037821 | 0.003922 |
| Minimum | -0.001625 | -0.001832 |
| Maximum | 0.002577 | 0.002677 |
| Sum | 0.00211404761 | 0.002542333 |
| Amount of days | 42 | 42 |

According to the results of the models shown in table we can see that the G (ARCH) model for this currency pair turned out to be more accurate. In this model, the standard error has decreased, and there is also a more accurate total amount.

The authors implemented modifications to the G (ARCH) model, which showed the best result

## III. DEVELOPMENT OF G (ARCH) MODEL MODIFICATION AND THE RESULTS

The model was modified on the basis of an empirical approach related to the fact that the value of a currency depends on many factors (events of a different nature taking place in the world) that the expert can somehow evaluate.

Such an assessment can be made at each step of the model, making certain adjustments to it (3). These changes can be made, for example, daily, so that the next day a more accurate result is obtained. The result of such a model will depend not only on mathematical calculations, but also on the experience of the person who implements it.

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + n_1) r_{t-1}^2 + \cdots + (\alpha_i + n_i) r_{t-1}^2 \qquad (3)$$

where $n_i$ is a parameter whose value the expert sets depending on events that, in his opinion, could affect the value of the currency.

TABLE II. THE RESULTS OF THE MODIFIED G (ARCH) MODEL (WITH DAILY EXPERT INTERVENTION) FOR 42 DAYS

| Parameters | ARMA Model | Model G (ARCH) |
|---|---|---|
| Mean | 0.0000301 | 0.0000299 |
| Standard error | 0.0000350 | 0.0000402 |
| Standard deviation | 0.0005111 | 0.0005222 |
| Scope | 0.003977 | 0.003922 |
| Minimum | -0.001944 | -0.001832 |
| Maximum | 0.00277 | 0.002677 |
| Sum | 0.0026562 | 0.002542333 |
| Amount of days | 42 | 42 |

Table 2 shows the result of the work of the data of the modified model (with daily expert intervention) in comparison with the base model G (ARCH).

Applying the modification of the G model (ARCH), the accuracy of the calculations increased by almost 4%. For the foreign exchange market, this is a good indicator.

A modified model with adjustments 2 times a day gives an even more accurate result (Table 3).

TABLE III. THE RESULTS OF THE MODIFIED G (ARCH) MODEL (EXPERT INTERVENTION 2 TIMES A DAY) FOR 42 DAYS

| Parameters | ARMA Model | Model G (ARCH) |
|---|---|---|
| Mean | 0.0000302 | 0.0000299 |
| Standard error | 0.0000340 | 0.0000402 |
| Standard deviation | 0.0005219 | 0.0005222 |
| Scope | 0.003988 | 0.003922 |
| Minimum | -0.001920 | -0.001832 |
| Maximum | 0.00276 | 0.002677 |
| Sum | 0.0027653 | 0.002542333 |
| Amount of days | 84 | 42 |

In this case, the model prediction accuracy increased by 7% relative to the base model G (ARCH).

An obvious factor is a significant increase in the complexity of this model. Optimization of the modified model is possible due to the replacement of the expert's work with elements of artificial intelligence. As an artificial intelligence, we are developing a neural network that will select this CF, instead of a human. A neural network will be able to more objectively consider factors and the same sample will be an order of magnitude higher.

Using a neural network, we plan to increase the accuracy of predictions to at least 10% relative to the base method.

## IV. CONCLUSION

The paper presents popular time series forecasting models. The authors developed an improved modification of the (G) ARCH model, which showed the best result for predicting the EUR / USD currency pair. To assess the performance of the models, a comparative analysis of the forecast data with the real one was carried out. The results showed some advantage in the accuracy of forecasting an improved model over existing analogues. This is very important, because this result allows us to evaluate the benefits of using additional parameters in classical models. Additional parameters are expert, but potentially they can be obtained analytically using various tools, for example, neural networks. The authors plan further work to improve models for forecasting the behavior of the foreign exchange market. As a result, we can say that our neural network will predict the currency price, otherwise than usual, since we will not train it on simple mathematical equations, but also take into account the opinions of a person who is versed in this area and will be able to adjust the model based on his experience, and not just numbers, we believe this is the uniqueness of this development.We use not just mathematics, but also human experience. Which can help find those factors that the neural network cannot see.

## REFERENCES


[1] V.P. Tsvetkov, V.N. Ryzikov, I.V. Tsvetkov and V.V. Ivanov, “Fractal methods in the study of socio-economic systems,” Modeling complex systems, vol. 2, pp. 72-81, 1999.

[2] Yu.P. Lukashin, “Adaptive methods for short-term time series forecasting,” Finances and statistics, Moscow, pp. 337-351, 2003.

[3] E.P. Churakov, “Econometric time series forecasting,” Finances and statistics, Moscow, 2008.

[4] A. Porshakov, E. Derugina, A. Ponomarenko and A. Sinykov, “Short-term estimation and forecasting of Russia's GDP using a dynamic factor mode,” Economic Research Report Series, no. 2, pp. 6-35, 2015.

[5] Y.A. Kropotov, A.Y. Proskuryakov and A.A. Belov, “Method for forecasting changes in time series parameters in digital information management systems,” Computer Optics, vol. 42, no. 6, pp. 1093-1100, 2018. DOI: 10.18287/2412-6179-2018-42-6-1093-1100.

[6] H. Akaike, “A new look at the statistical model identification,” IEEE Transactions on Automatic Control, pp. 713-723, 1974.

[7] T. Bollerslev, “Generalized Autoregressive Conditional Heteroskedasticity,” Journal of Econometrics, pp. 307-327, 1986.

[8] A.N. Sotnikov, “Dynamics modeling and price prediction of a particular type of product,” Statistics Issues, no. 6, pp. 7-12, 2002.

[9] D.A. Hsieh, “The statistical properties of daily foreign exchange rates,” Journal of International Economics, pp. 129-145, 1988.

[10] R.A. Meese and K. Rogoff, “Empirical exchange rate models of the seventies: do they fit out of sample,” Journal of International Economics, vol. 25, pp. 3-24, 1983.

[11] B.M. Mizrach, “Multivariate nearest neighbour forecasts of EMS exchange rates,” Journal of Applied Econometrics, pp. 151-163, 1992.

[12] P. Frances and D. Dijk, “Non-linear Time Series Models in Empirical Finance,” Cambridge University Press, 2003.

[13] M.W. Brandt and J. Kinlay, “Estimating Historical Volatility,” Duke University, Investment Analytics, 2005.

[14] R.S. Tsay, “Analysis of Financial Time Series,” Wiley, 2005.