TEST Engineering & Management

November-December 2019
ISSN: 0193-4120 Page No. 3672 - 3680

Predictive Models of Development of the Market of Crypto Currency (ARMA, LSTM): Comparative Analysis

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Article Info
Volume 81
Page Number: 3672 - 3680
Publication Issue:
November-December 2019

Abstract:
Today we can see a profound transformation of the traditional world of money and finance. Innovations in the financial sector, new technologies, tools and systems entail serious and profound changes in the usual financial institutions. One of the most important stages of these transformations was the emergence of cryptocurrencies, accompanied by the rapid development of related technologies and the lack of a clear picture of its future landscape.
The lack of a unified approach to the study of the formation of the cryptocurrency rate, the imperfection of the methods for its forecasting impede understanding and objective perception of the prospects for their development.
The relevance of the topic is due to the increasing pace of development of the cryptocurrency market, and the need to create a model capable of predicting the course of major cryptocurrencies.
To solve this problem, a comparative analysis of prognostic models based on the construction of neural networks and the autoregressive-moving average model is proposed. The calculation procedure involved the construction of a recurrent neural network - LSTM, capable of learning long-term dependencies.
As the initial data necessary for the experiment, data on the Bitcoin cryptocurrency rate were used. Econometric processing of the results was based on the integration of descriptive statistics. Based on the results of the study, a predictive model is built to predict the short-term course of bitcoin.

Article History
Article Received: *5 March 2019*
Revised: *18 May 2019*
Accepted: *24 September 2019*
Publication: *18 December 2019*

Keywords: *cryptocurrency, bitcoin, economic and mathematical methods, forecasting, ARMA modeling.*

The publication was prepared as part of the scientific project supported by the Russian Foundation for Basic Research No. 18-010-00536

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1. INTRODUCTION

The accelerated pace of development of the cryptocurrency market and its integration into the system of economic, operational, financial, and other processes determines the need for a comprehensive study of this phenomenon.

The main advantages of cryptocurrencies are, first of all, reducing transaction costs, accelerating the speed of transactions, their security, as well as data security due to the decentralization of tracking and maintenance tools, high anonymity and confidentiality, lack of inflationary pressure. Various experts have studied the weaknesses of cryptocurrencies, their list changes as the market develops; among the main ones are features such as dependence on external network factors, extremely high price volatility, cybersecurity, lack of lending and regulatory institutions.

Despite the fact that cryptocurrencies do not have all the necessary attributes of money, a lot of research is being done on comparing cryptocurrencies with traditional currencies. The main advantage of cryptocurrencies is the cost savings for their manufacture, transportation, and maintenance due to the digital nature of these currencies, low transaction costs, high transaction speed, low commission fees. From the point of view of security, on the one hand, the lack of their physical form reduces the risk of theft during payments, which is its advantage over traditional money, and on the other hand, due to the fact that cryptocurrency transactions are conducted through the Internet, the question arises of ensuring cybersecurity that exacerbated by the lack of a regulatory body, whose area of responsibility would include ensuring the security of transactions with cryptocurrencies.

2. METHODS

The topic of searching for and scientific substantiation of tools and algorithms for developing prognostic models of financial time series attracts the attention of many researchers in different countries, and a large number of works are devoted to the search for such mechanisms.

A significant number of researchers in their works focus on traditional methods of forecasting financial series - technical and fundamental analysis [1, 2]. In their works, they showed that these methods can accurately predict the exchange rates of national economies.

In addition, in recent years there has been growing interest in using stochastic forecasting methods in various industries, including modeling of financial and economic series. Stochastic models allow building reliable forecasts that take into account the high volatility of the data. The use of such models can be either an alternative or an addition to traditional forecasting methods. In this regard, some researchers use methods of economic-mathematical analysis in their works [3, 4]. Bouoiyour in his work summarized research on this topic [5].

A number of works are devoted to the search and development of the methodological apparatus, with the aim of modeling the course of cryptocurrencies. Due to the high volatility of such series, the use of traditional methods does not always ensure high accuracy of the forecast. As a consequence, most of the work is concentrated in the field of time series analysis.

In [6], an attempt was made to simulate the Bitcoin cryptocurrency based on the relationship of the exchange rate with external factors, such as legal regulation, mining complexity (hashrate), etc.

The main advantage of econometric models based on time series analysis is their ability to simulate high cost volatility.

In our previous works, we have already considered forecasting methods using the example of the Bitcoin cryptocurrency using stochastic modeling of time series [7].

3. RESULTS

The calculations were carried out for the "Bitcoin" time series. The initial data was cryptocurrency quotes from January 2, 2015 to December 30, 2018 (Figure 1) [10].

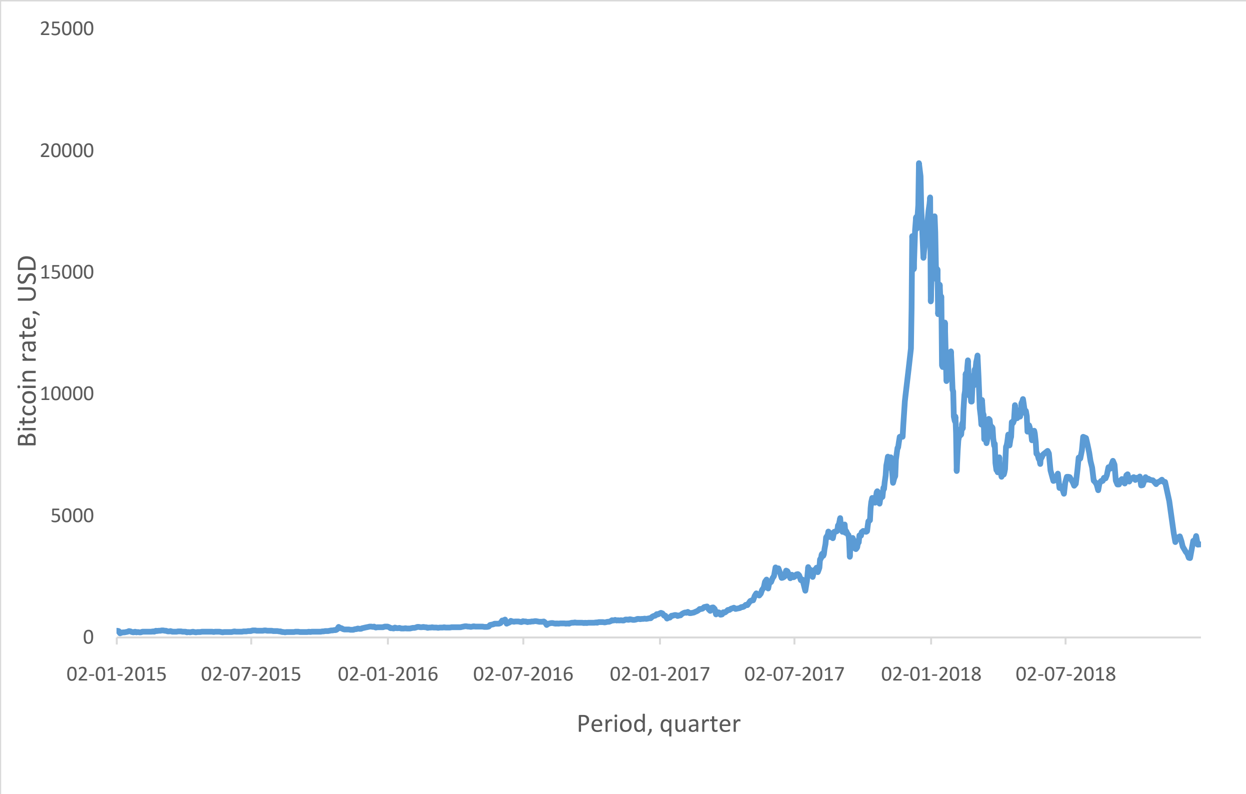

Figure 1 - Bitcoin cryptocurrency exchange rate over time from January 2, 2015 to December 30, 2018.

Source: https://www.blockchain.com/ru/

In order to choose the best prognostic model in this study, a comparative analysis of the stochastic model (autoregressive integrated moving average (ARIMA)) and a model built on a neural network

3.1. Neural network modeling

Long-short-term memory networks, or LSTM, can be used to predict time series. There are many types of LSTM models that can be used for each specific forecasting task.

For time series, for example, quotes of currencies, dependence on past data is characteristic; this phenomenon is called a long-term trend.

Cells of recurrent neural networks represent this dependence using a hidden state, or memory, which stores a summary of past information. The value of the hidden state at any time is a function of its value in the previous step and the data value in the current step:

$$\boldsymbol{h_t = \varphi(h_{t-1}, x_t)},$$

where h_t and h_{t-1} are the latent state values at step t and t - 1, respectively, and x_t is the input value at time t. Note that this equation is recursive, that is, h_{t-1} can be expressed in terms

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of h_{t-2} and x_{t-1}, etc., until we get to the beginning of the sequence. Thus, recurrent neural networks encode and store information on an arbitrarily long sequence.

LSTM is a variant of a recurrent neural network that can learn long-term dependencies [20]. LSTM networks perform well a wide range of tasks and are the most popular type of recurrent neural network. LSTM uses a combination of the hidden state in the previous step and the current input in the layer with the activation function to implement recurrence. Figure 2 shows the transformations applied to the latent state on the timeline t.

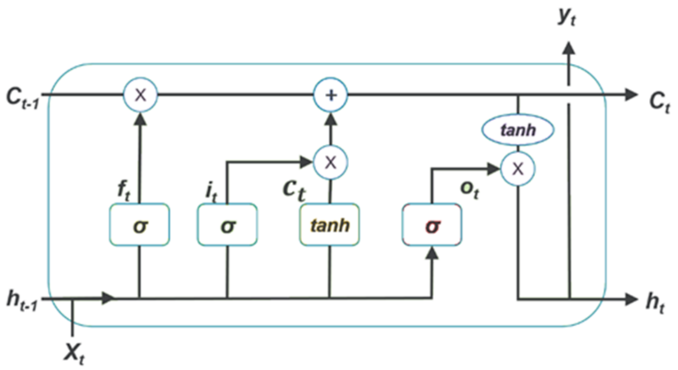

Figure 2. LSTM network architecture.

The horizontal line at the top shows the state of the cell; it represents the internal memory of the block. The line below shows the latent state, and the gates f, i, c, o are the mechanisms due to which the LSTM network bypasses the problem of the disappearing gradient. В процессеобучения LSTM находитпараметрыэтихвентилей:

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f),$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i),$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o),$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c),$$
$$h_t = o_t \circ \sigma_c(c_t),$$

x_t - input vector,

y_t - output vector,

c_t - state vector,

f_t - forgetting gate vector, weight of remembering old information,

i_t - input gate vector, weight of receiving new information,

o_t- output gate vector,

σ_g - an activation function based on a signoid,

σ_c - an activation function based on hyperbolic tangent.

The present study used the following parameters to select parameters by random search:

1. Loss function: Logcosh, MAE, MSE, MSLE.
2. Optimizer: SGD, Adam, Adagrad, AdaDelta, RMSprop, Adamax, Nadam.
3. Activation function: ELU, SELU, Softplus, Softsign,ReLu,Tanh, Sigmoid, Hard sigmoid, Linear.
4. The number of neurons in the hidden layer is from 1 to 30.
5. The number of epochs is from 100 to 500.
6. The amount of data in one batch is from 50 to 300.
7. Dropout is from 0 to 20.

In total, more than 200 experiments were conducted. The results of the 15 best experiments performed are presented in Table 1.

Table 1 - The results of the 15 best experiments performed

loss	activation	optimazer	neurons	epochs	batch_size	dropout	rmse
logcosh	relu	Nadam	16	488	216	17,00	139,35
logcosh	linear	Nadam	26	310	100	19,00	139,87
mse	linear	Nadam	6	381	80	3,00	141,21
mse	linear	Nadam	14	373	80	8,00	141,34

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mae	tanh	AdaDelta	5	494	110	11,00	141,71
logcosh	tanh	Nadam	30	382	144	0,00	142,44
mae	linear	Nadam	12	455	123	4,00	142,48
mse	selu	Nadam	21	231	116	1,00	142,95
logcosh	selu	Nadam	8	486	115	2,00	143,25
mse	elu	Nadam	22	449	144	15,00	143,39
logcosh	elu	RMSprop	10	429	137	17,00	143,57
msle	linear	Nadam	26	461	116	17,00	143,67
mse	tanh	RMSprop	17	480	106	9,00	143,92
msle	tanh	RMSprop	24	460	71	14,00	143,97
mae	relu	Nadam	16	369	192	16,00	144,20

Figure 3 shows the graphs of the calculation errors for the test and training samples. As the approximation function, the logarithm function of the hyperbolic cosine was chosen, the number of neurons was 16, the optimizer was Nadam. We can see that with an increase in the number of iterations, the margin of error decreases (the error for the training and test data is 5.652479786606858e-05 and 7.527783456680481e-05, respectively).

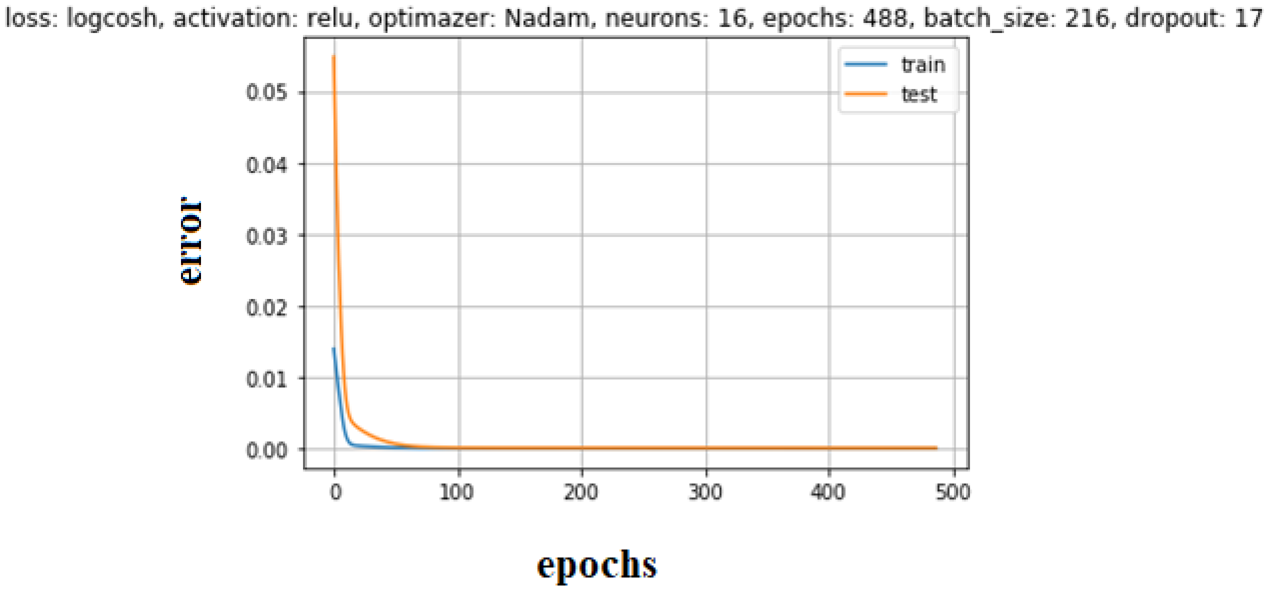

Figure 3. Calculation error diagrams for test and training samples

Figure 4 shows graphs of the lowest price in the period from February 11, 2018 to March 17, 2019 and the forecast value of the trained model. The logarithm function of the hyperbolic cosine was chosen as the objective function, the number of neurons in the hidden LSTM layer was 16, and the optimizer was Nadam. This diagram shows a high correlation between real and predicted values.

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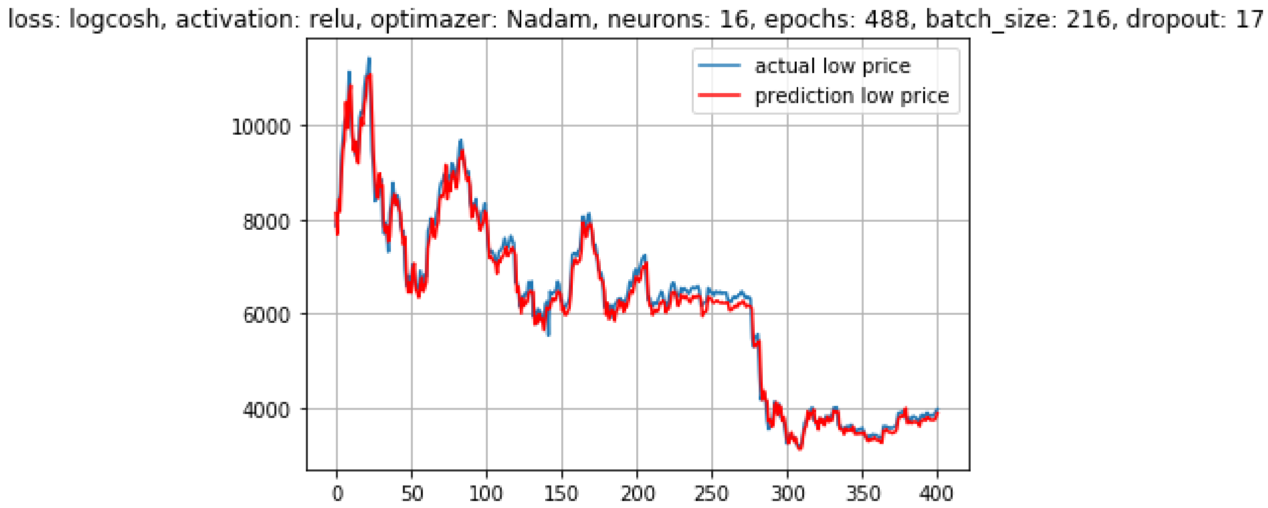

Figure 4. Diagrams of the lowest real and predicted value of bitcoin against the dollar from February 11, 2018 to March 17, 2019.

3.2. Autoregressive-moving average model

Modeling of stationary time series or series that can be reduced to stationary can be performed using the class of autoregressive-moving average models (ARMA), which is a combination of two models: autoregression of order *p* and moving average order *q*. In a generalized form, the ARMA (*p*, *q*) model is as follows:

$$Y_t = a_0 + a_1 X_{t-1} + a_2 X_2 \ldots + a_n X_{t-n} + \varepsilon_t - \beta_1 \varepsilon_{e-1} - \beta_2 \varepsilon_{e-2} - \ldots - \beta_n \varepsilon_{t-n}$$

For non-stationary data, Box and Jenkins proposed the ARIMA model (*p, d, q*), which after taking *d* consecutive differences can be reduced to the stationary form [7], where *p, d, q* are structural parameters characterizing the order for the corresponding parts of the model - autoregressive, integrated and moving average.

The methodology for selecting a model consists of several stages.

At the initial stage of the study, it is necessary to find out whether the series under study has the property of stationarity.

The stationarity assessment of a series can be carried out using various methods. The basic methods for checking the stationarity of BP are the advanced Dickey-Fuller test, as well as the construction of an autocorrelation function (ACF) and a partial autocorrelation function (PACF). The calculation of the autocorrelation function is performed according to the following formula:

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{cov(k)}{var} = \frac{cov(y_t; y_{t-k})}{var(y_t)}; \ |\rho_k| \leq 1 . \quad (2)$$

A partial autocorrelation function (PACF) is defined as a partial correlation between the values y_t and y_{t-k} "cleared" of the influence of intermediate variables on them [8].

For the time series under study, ACF and PACF were constructed (see Fig. 5).

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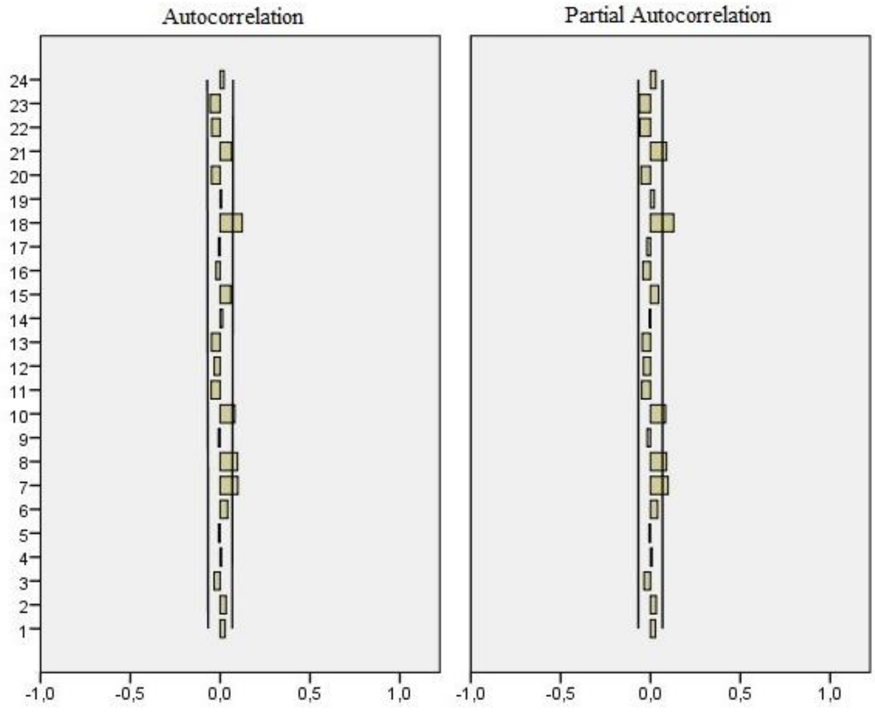

Figure 5. Autocorrelation and partial autocorrelation functions

To model the dynamics of changes in the rate of cryptocurrencies, the following models were tested: ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,0) ARIMA (2,1,1), ARIMA (2,1,2). According to the results of the analysis, the ARIMA model (2.1.2) turned out to be the best.

The basis for the choice of the model was the functions constructed by the ACF and PACF, as well as the calculated Akaike criterion (3) and the Bayesian information criterion (4).

These criteria allow choosing the best model from the group of candidate models. Advantage is given to the model with minimal AIC and BIC values. The calculation is made according to the following formulas:

$$AIC = ln\widehat{\delta^2} + \frac{2}{n}r, \quad (3)$$

$$BIC = ln\widehat{\delta^2} + \frac{\ln n}{n}r\,. \quad (4)$$

where $\widehat{\delta^2}$ is is the residual sum of squares divided by the number of observations,

r is the total number of summands of the ARIMA model.

Thus, the final model took the following form:

$$\Delta X = 4{,}318 - 1{,}581\Delta X_{t-1} - 0{,}855\Delta X_{t-2} - 1{,}664\varepsilon_{t-1} - 0{,}873\varepsilon_{t-2} + \varepsilon_t.$$

Table 2

Parameters of the autoregressive integrated moving average model

		Coefficient
ARIMA (2,1,2)	C	4,318
	AR	-1,581
		-,855
	d	1
	CC	-1,664
		-,873

Using the obtained model, the cryptocurrency rate of bitcoin was predicted 5 points in advance. The forecast results are shown in Figure 6.

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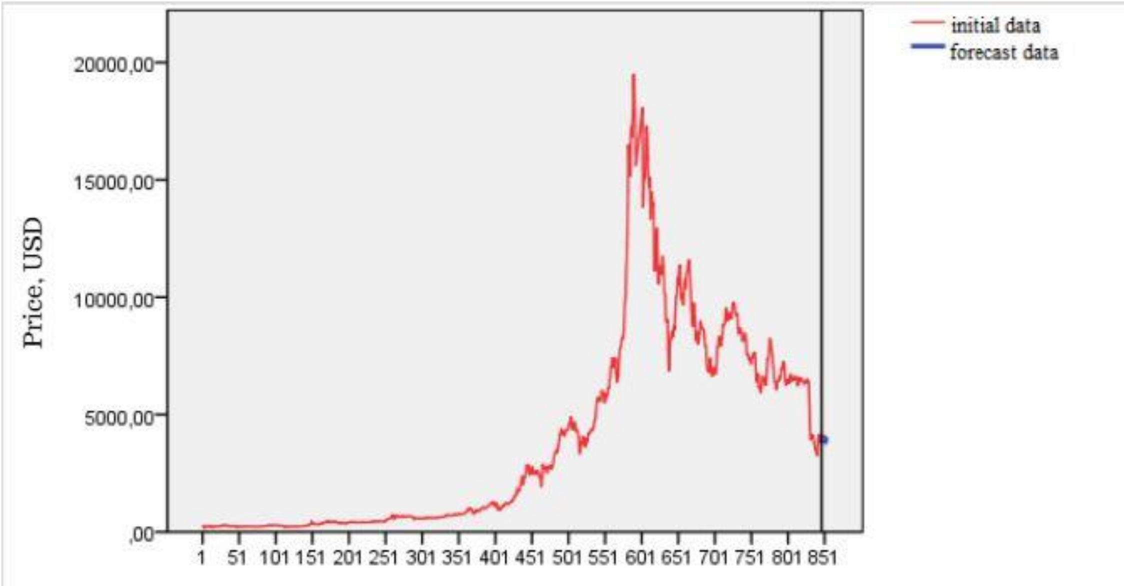

Figure 6 - Real and forecast values of the ARIMA model

Table 3
Forecast values

Model		847	848	849	850
ARIMA (2,1,2)	Predicted values	3989,15	3893,03	3926,22	3970,77
	UCL	4686,51	4921,29	5156,88	5412,97
	LCL	3291,78	2864,78	2695,57	2528,56

Qualitative characteristics of the obtained predictive model are shown in Table 4.

Table 4

Qualitative characteristics of the ARIMA model (2,1,2).

Statistic	**Average value**	Min	Max	Percentile						
				5	10	25	50	75	90	95
R-Squared	,993	,993	,993	,993	,993	,993	,993	,993	,993	,993
RMSE	355,293	355,29	355,293	355,293	355,293	355,293	355,293	355,293	355,29	355,29
MAPE	3,825	3,825	3,825	3,825	3,825	3,825	3,825	3,825	3,825	3,825
MaxAPE	55,226	55,226	55,226	55,226	55,226	55,226	55,226	55,226	55,226	55,226
MAE	159,332	159,33	159,332	159,332	159,332	159,332	159,332	159,332	159,33	159,33
MaxAE	4158,47	4158,4	4158,473	4158,473	4158,473	4158,473	4158,473	4158,47	4158,4	4158,4
BIC	11,786	11,786	11,786	11,786	11,786	11,786	11,786	11,786	11,786	11,786

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SUMMARY

This study involved a comparative analysis of models for predicting the Bitcoin cryptocurrency. The results allow us to conclude that the model built on a neural network, as well as the stochastic ARIMA model (2,1,2) accurately simulate the initial series. Thus, the forecasts obtained using such models can be quite effective.

CONCLUSIONS

We should note that the findings are largely based on the approaches proposed in the study, based on the application of prognostic models in the construction process.

Thus, it can be stated that the algorithm embedded in the research tools forms a stable basis for formalized estimates and calculations.

ACKNOWLEDGMENTS

The work was performed at the expense of the subsidy allocated to Kazan State University for the state assignment in scientific activity (No. 26.8732.2017/БЧ).

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