Risks of the methodology for forecasting the price of bitcoin and the frequency of its online requests in the digitalization of economic systems

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Abstract. *Research goals and objectives*: to study the series of dynamics of the frequency of requests and the price of bitcoin under the conditions of taking into account the risks of using various forecasting methods.
Subject of research: proof of importance of the role, statistical dependence and interdependence of the series of dynamics of the price of bitcoin and the frequency of its online requests.
Research methods used: analytical methods, econometric models, nonlinear dynamics methods.
Results of the research: The research grounded the approach and the forecasting procedure for the series of dynamics of the price of bitcoin and the frequency of its online requests, which in essence correspond to the basic principles of the implementation of the forecasting methodology, take into account the specifics of the formation of the frequency of online requests for bitcoin prices and the socio-economic meaning of its functioning. The practical value consists in determining that the minimum risks for the study of a time series dynamics of bitcoin price and frequency of requests for bitcoin price were demonstrated by the neural network methodology in comparison with the use of the ARIMA model and other methods of economic and mathematical modeling that proves the proposed methodology for determining the direction of the trend outside the study period.

Keywords. bitcoin price, frequency of requests, time series of dynamics, forecasting, risks, methodology, neural networks, ARIMA models.

1 Introduction

The cryptocurrency phenomenon has proved the promise of the search for alternative exchange units, whose circulating capabilities will not be limited by state money supply regulation mechanisms and exchange rate policies of national banks, and, in general, will operate according to the principles of decentralization in the online environment. Only market conditions in their pure form make it possible to reliably assess the investment attractiveness and financial prospects of new instruments, the functioning space of which are not limited to the real market, but cover the online environment. This is completely logical, since bitcoin is a product of cryptography, the development of digital technologies, and the spread of their use in economic systems.

The atypical and contradictory nature of bitcoin requires a thorough study of its parameters and features of functional development in a real socio-economic environment of practitioners and scientists who still have not come to a final thought about the benefits and the risks that accompany them [1]. The cryptocurrency decentralization mechanism, which is manifested in the confidentiality and unrestrictedness of purchases and sales, includes all the same elements of centralized functioning due to the involvement of intermediaries in the mechanism. Intermediaries, in particular, for the provision of digital wallet services, Mixers, Mining Pools and others, which together provide minimization of constant costs, expand the capabilities of users and etcetera, but also have a cost and additional risks [2]. Over time, the complexity of the functional mechanism of cryptocurrencies only increases, so the systemic and non-systemic risks change, form a new list of threats. However, interest in cryptocurrencies is not waning.

Thus, the growing attention of the world community to the digitalization of socio-economic processes is a prerequisite for the emergence of a new alternative exchange currency – cryptocurrency. Their gradually increasing availability in the markets, despite the attendant risks, has formulated a steady demand for cryptocurrency for both the object of investment and exchange. Therefore, the mechanism of functioning of the cryptocurrency and cursive differences require a systematic monitoring of key parameters, which is easiest and fastest to do in an online environment.

Now, sufficient technical attention to cryptocurrency has supplemented with economic content and outlined the circle of social issues that arose in the formation of the cryptocurrency market. In general, Marella V., Lindman J., Rossi M., and Tuunainen V. consider that "Bitcoin is a social movement in the financial industry" [3]. As a result, despite the insufficient level of awareness, technical and financial literacy of the population of developing countries, and thanks to the principle of decentralization, the dynamics of interest in cryptocurrencies in the online environment, in particular, bitcoin, are changing in accordance with changes in trends in their exchange rate, which is currently little studied.

The purpose of the paper is to study the time series of dynamics of the frequency of requests for bitcoin, taking into account the risk of using various forecasting methods. The object of the research is the time series of the frequency of requests for bitcoin in Ukraine according to Google Trends and bitcoin price. The subject of the research is the risks of forecasting series of dynamics.

2 Related Work

The dynamic series of cryptocurrencies are investigated by a wide range of methods, which today has formed a certain knowledge base of their accuracy, adequacy and appropriateness of application. But, given the constant updating of statistical data, the search for an adequate methodology for forecasting cryptocurrency parameters will be relevant and timely at every stage of development.

Today, the results of researches of the bitcoin price time series dynamics in the context of explaining the laws of its changes by the situation of modern economic theories have proved their practical value; also, the activity and behavior of market agents in general were taken into account, in particular, the influence of social networks and the structure of the formed cryptocurrency market, which is constantly evolving, was noted and is being improved [5]. The methods of machine learning and modeling are actively used to forecast the trajectory of changes in the parameters of bitcoin (most often, the dynamics of the price) and the cryptocurrency market [4, 5]. In particular, there are results of using:

- linear models [8], but non-linearity is inherent in socio-economic processes, which limits the possibility of applying the approach;
- nonlinear autoregression [9], where the accuracy and quality of approaches is limited when applied to data such as random walk;
- binomial logistic regression [10], the implementation of a Bayesian optimized recurrent neural network, Long Short Term Memory network and the ARIMA model [6], effect of Bayesian neural networks [7], where from the practice of using approaches it is proved that in the accuracy of forecasts ARIMA models are significantly inferior to the results of using neural networks;
- methods of the theory of complex systems have been successfully used to justify the forerunners of critical changes in the bitcoin exchange rate [11], but qualitative results were obtained on the trend in 2017 and it is not known what results will be for the updated trend of the input data and whether the technology can determine the direction of the trend.

Separately, note that a connection has already been established between bitcoins and search information in Google, Wikipedia materials about them in an online environment [12]. In addition, researches of the interdependence of requests in social networks and the bitcoin exchange rate [13] are valuable, where a positive effect of the growth of its popularity on the growth of search queries was established. In the article [14], the authors studied the self-similarity and multifractal features of the bitcoin exchange rate series, which corresponds to the nature and degree of complexity of the bitcoin ecosystem. Also, the authors of [14] proved the feasibility of taking into account indicators of social networks in order to predict the exchange rate of bitcoin using fractal analysis methods.

The results of forecasting accuracy and the adequacy of forecasting models differ methods at different periods of bitcoin course research, but scientists focus mainly on machine learning methods. However, today the social aspect of the cryptocurrency market is actively being studied, the quantitative and qualitative impact of this phenomenon on various areas of socio-economic existence.

3 Risk

Forecasting as a methodology is constantly tested for adequacy to the realities of socio-economic processes, since their complexity and unpredictability only increase over time. The emergence of new tools requires taking into account not only the results of the analysis of the series of dynamics that they produce, their economic meaning, but also against the background of taking into account the risks of functioning of the research object itself, the risks of using the chosen forecasting methodology.

Thus, the risk structure is presented as a set of risks directly using the forecasting methodology, and a set of risks that are inherent in the bitcoin functioning system (forming a circle of relevant interests of online market agents), namely: internal and external (technological, social, economic, interest in security, political and so on):

$$R = \left\langle R^S, R^M, t \right\rangle, \tag{1}$$

where $R^S = \{r_i^S\}$ – the set of systemic risks inherent in the price of bitcoin (the frequency of requests for bitcoin), which are allocated from the socio-economic environment for the period t;

$R^M = \{r_j^M\}$ – the set of methodological risks of forecasting for the period t.

The list of risks of the forecasting methodology includes such factors as: the probability of making a mistake in choosing formal-informal methods and models; the probability of achieving the goal of the study; the reliability of the results; accuracy of their interpretation; excessive subjectivity in prediction; reassessment of the capabilities of the resulting models; quality and reliability of information support and etcetera. Most of these risks relate to the subjective and organizational aspects, therefore, their level directly depends on the subject who makes the decision and the availability of methodological tools, the measure of their mastery, reliable initial data for the required period. Prediction as a phased process forms the level of aggregate risk with a cumulative total, therefore its final value is determined by the product of risk indicators of each stage of its implementation. Significant of taking into account methodological risks involve that the prognostic results are based on entities making financial and investment decisions, which together form the behavior and set the cryptocurrency spread rates, the unregulatedness of which also forms a circle of risks for users. Therefore, the issue of choosing a forecasting methodology is given special attention.

4 Method

The forecasting methodology should include the use of several methods to develop a forecast and select the best of them based on estimates of the accuracy and quality of the forecast. Thus, the authors proposed a methodology for predicting the price of bitcoin and the frequency of online requests for bitcoin, which consists of four interrelated steps (fig. 1).

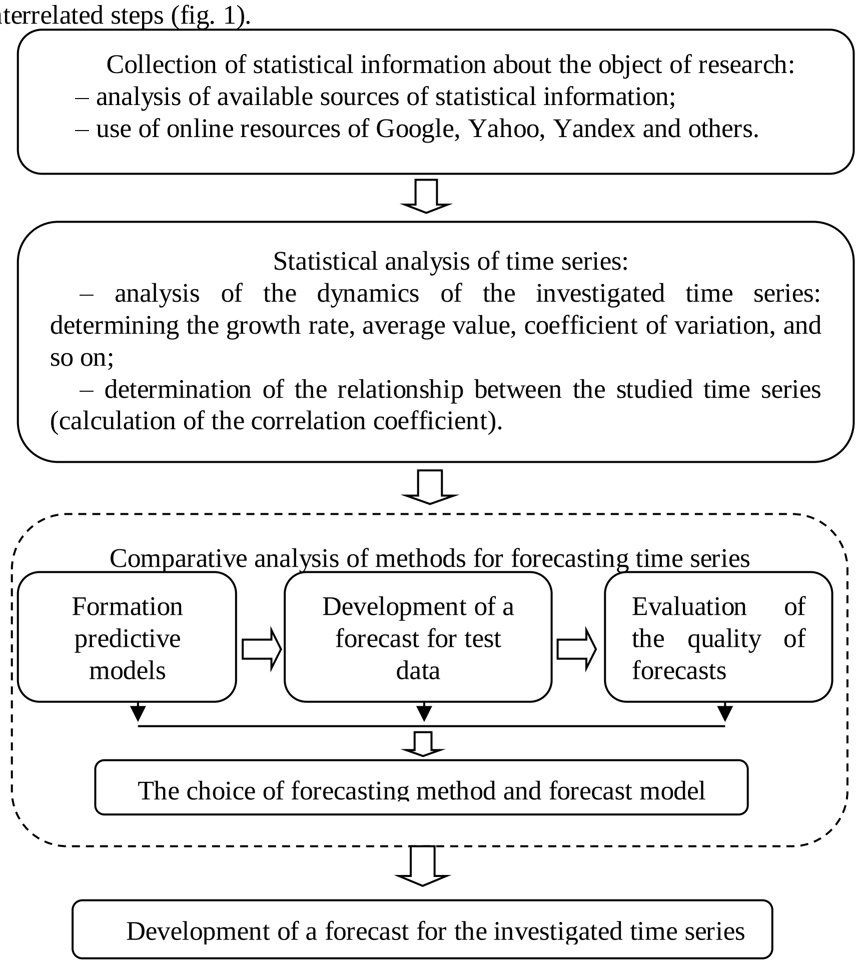

Fig. 1. Methodology of time series forecasting

The set of initial statistics consists of two time series, namely: the frequency of online requests for bitcoin in Ukraine and the price of bitcoin. Time series were generated using data from Google Trends [15] and InvestFunds [16] for the period from January 18, 2015 to January 12, 2020.

Statistical analysis of the studied time series will reveal the maximum, minimum and average values of the series, as well as establish the growth rate, measure the variability of the series and measure the relationship between the studied series. If necessary, standardizing of time series is carried out.

Further, in accordance with fig. 1, forecast models are directly developed. To study the series of dynamics, the authors selected several approaches to forecasting (econometric models and non-linear dynamics methods), among which the best results were shown by neural networks and ARIMA models. Thus Auto-Regressive Integrated Moving Average (ARIMA) model and Neural Network Auto-Regressive (NNAR) model were chosen.

The Auto-Regressive Integrated Moving Average (ARIMA) model describes the time series by two main processes, namely: the process of autoregression and moving average. Most time series contain elements that are sequentially dependent on each other. This dependence can be expressed by the equation:

$$x_t = \delta + \beta_1 \cdot x_{(t-1)} + \beta_2 \cdot x_{(t-2)} + \beta_3 \cdot x_{(t-3)} + ... + \varepsilon_t \, , \tag{2}$$

where δ – constant;

$\beta_1, \beta_2, \beta_3$ – autoregressive parameters;

ε – random component.

Thus, each observation is the sum of a random component and a linear combination of previous observations. The autoregression process will be stationary only when its parameters are in a certain range. For example, if there is only one parameter, then it must be in the range $-1 < \beta < +1$. In the opposite case, the previous values will accumulate and the values of the next x_t can be unlimited, respectively, the time series will not be stationary.

Unlike the autoregression process, in the moving average process, each element of the series falls under the combined influence of previous errors. In general terms, this can be represented as follows:

$$x_t = \mu + \alpha_1 \cdot x_{(t-1)} + \alpha_2 \cdot x_{(t-2)} + \alpha_3 \cdot x_{(t-3)} + ... + \varepsilon_t \, , \tag{3}$$

where μ – constant;

$\alpha_1, \alpha_2, \alpha_3$ – moving average parameters;

ε – random component.

That is, the current observation of a time series is the sum of a random component at a given point in time and a linear combination of random influences at previous points in time. It should be noted that between the processes of the moving average and autoregression there is “duality” – one equation can be rewritten in the form of another and vice versa (reversibility property). Similar to the stationary conditions, there are conditions that ensure the reversibility of the model.

The generalized ARIMA model includes both autoregressive parameters and moving average parameters. The model is described using three parameters: autoregressive parameters (p), difference order (d) and moving average parameters (q). This model is described as follows: ARIMA (p, d, q).

The next forecasting method is the Neural Network Auto-Regressive (NNAR) model. Artificial neural networks allow to explore complex non-linear relationships between incoming and outgoing variables. They are widely used for approximating functions and forecasting. The main advantage of these models is that they allow the approximation of a large class of functions with a high level of accuracy. In this model, older values of the time series are used as input data of the model, and forecast values are used as outgoing values. The NNAR model can be represented as a neural network, which includes a linear combination function and an activation function [17, 18, 19]. The linear combination function can be given in the following form:

$$net_j = \sum_i w_{ij} x_{ij} \ . \tag{4}$$

The activation function is a sigmoid function and is defined as follows:

$$f(x) = \frac{1}{1 + \exp^{-x}} \ . \tag{5}$$

The network inputs are connected using a linear function and, as a result of various combinations, are then transmitted through a sigmoid nonlinear activation function. In accordance with the article [20], the weights of the neural network are updated using the inverse propagation algorithm. Weights in the neural network are selected so that the forecast error is minimal.

This article uses the following model designation: NNAR (p, k), where the first parameter (p) shows the number of lags and the second (k) – the number of nodes in the hidden layer.

Having built forecast models ARIMA and NNAR, they should be verified and the quality and accuracy of the forecast should be determined. As estimates of the accuracy of the forecast, mean absolute percentage error (MARE) is used, which is determined by the following formula:

$$MAPE = \frac{100}{\tau} \sum_{t=T+1}^{T+\tau} \left| \frac{x_t - \hat{x}_t}{x_t} \right| . \tag{5}$$

As a result of model verification, the model that has the minimum forecast error is selected [21].

5 Results

The forecasting methodology proposed by the authors was tested for two time series: the price of bitcoin and the frequency of requests for bitcoin of Ukrainian online users in Google Trends. The initial data are weekly values, and the observation base was 261 periods. Thus, the regulatory independence of Bitcoin has led to a close relationship between its price and demand, which proves the similarity of the series of request frequency and bitcoin price in fig. 2. The circle of interests in cryptocurrencies in the online environment is characterized by the structure of the semantic core of requests from market agents, the frequency of which in different periods determines the direction of their changes, which is explained by the socio-economic factors of influence of the studied period. Consequently, the level of interest in the object and the frequency of its online queries is characterized by a direct proportion. The most popular structure of the semantic core is the simplest semantic unit, therefore it has a significant number of semantic links and corresponds directly to the name of the electronic currency - "bitcoin". The relationship of more complex requests with the core "bitcoin" has not been investigated.

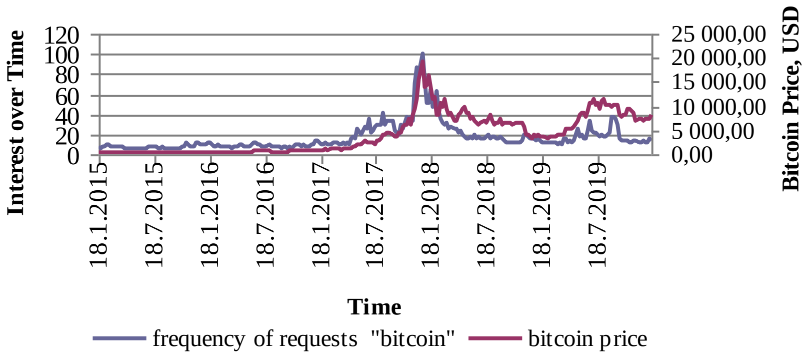

Fig.2. The time series of dynamics of the price of bitcoin and the frequency of online requests "bitcoin" according to Google Trends in Ukraine

In accordance with the data in fig. 2, as we can see the price of bitcoin is quite volatile. So, on August 06, 2012, its maximum value is traced at the level of 3,213.94 USD, and on January 18, 2015, the minimum value is recorded – 210.34 USD. It was found that for the study period, the price of bitcoin increased weekly by an average of 2%, and the frequency of requests - by 2.1%. The maximum increase in bitcoin value is 41.5% (July 23, 2017), the minimum increase is 29.8% (April 02, 2018), and the average price of bitcoin was 4023.752 USD. In the studied time series of the price of bitcoin, there is a high variability of values, as evidenced by the coefficient of variation, which is 91%.

It was during the period when the bitcoin price reached its maximum that the frequency of requests in the online environment for the keyword "bitcoin" also reached its maximum value - 100 interest over time. At the same time, the minimum value of the number of bitcoin price request frequency rates (5 interest over time) was observed in several periods: April 19,2015, May 17, 2015, June 06, 2015, June 14, 2015, September 06, 2015, September 13, 2015, April 10, 2015, November 10, 2015. These dates correspond to the period when the bitcoin price dynamics is characterized by a low level of volatility. For the analyzed period, it was found that on average there were 17 interest over time per week. Thus, it can be argued that the interest in bitcoin in the online environment increases and forms a number of dynamics similar to the dynamics of its value in periods of significant fluctuations. The stability of its exchange rate does not arouse the interest of market agents, therefore, they conduct certain periodic monitoring.

The correlation coefficient between the studied series of dynamics (fig. 2) is 0,73, which proves the tightness of the relationship and the interdependence of their trends. A more pronounced similarity of trends is observed during periods when the Bitcoin exchange rate was characterized by significant volatility. Consequently, the variability of exchange rate fluctuations, among other factors, causes an increase in interest from market agents, which is expressed by a corresponding change in the frequency of their requests in the online environment. The weight of the research of the influence of the dynamics of the frequency of requests "bitcoin" is explained by the fact that this semantic core with a significant level of popularity in the online environment determines the behavior of market agents. In addition, the frequency of the indicator may form an idea of the possible demand for cryptocurrency.

The indicated sensitivity of the frequency of online requests to exchange rate fluctuations of bitcoin is more pronounced than in other currencies, in particular, between the exchange rates of the euro, the dollar and the frequency of their online requests (fig. 3).

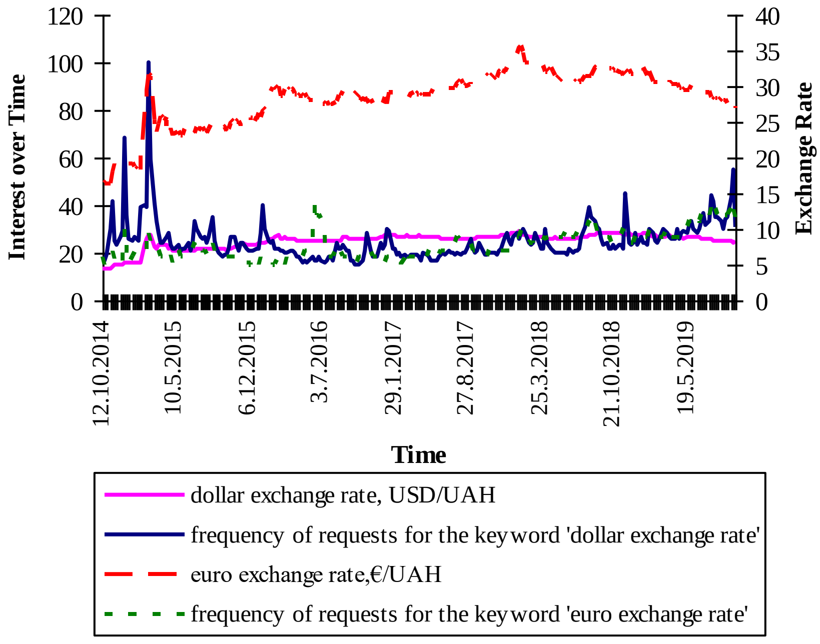

Fig. 3. The time series of dynamics of the exchange rates and the frequency of online requests "dollar" and "euro" according to Google Trends in Ukraine

The aforementioned is explained by the limiting influence of the monetary policy of the states and the International Monetary Fund, therefore, the connection density is present, but not significant (k = 0.37). And this is logical, since at the given moment all states are trying to limit the possibility of the outflow of the national currency from the country by means of cryptocurrencies and technologies [22; 23].

In accordance with the proposed methodology (fig. 1), the next step is to build models for predicting the studied time series, namely, the price of bitcoin and the frequency of requests. To build the models, used the tools of the R environment, namely the "forecast" library. The time series was divided into training and test sets. The training set was 96% of the data (251 values, data from January 18, 2015 to November 03, 2019), and the test set was 4% of data (10 values, from November 10, 2019 to January 12, 2020).

By analyzing the data in fig. 2, we can state that there are peaks and drops in the trend direction in the time series. The investigated time series are non-stationary, which confirms the advanced Dickey-Fuller Test. On the other hand, with a fairly high level of confidence, it can be argued that the first-order differences of the series are stationary, that is, these are integrated first-order time series. There is no seasonal component in the time series, but a random component is present. In the medium term, compared the predictive models of ARIMA and the neural network.

In fig. 4 and fig. 5 shows the constructed predictive models for the test set of the time series – the price of bitcoin.

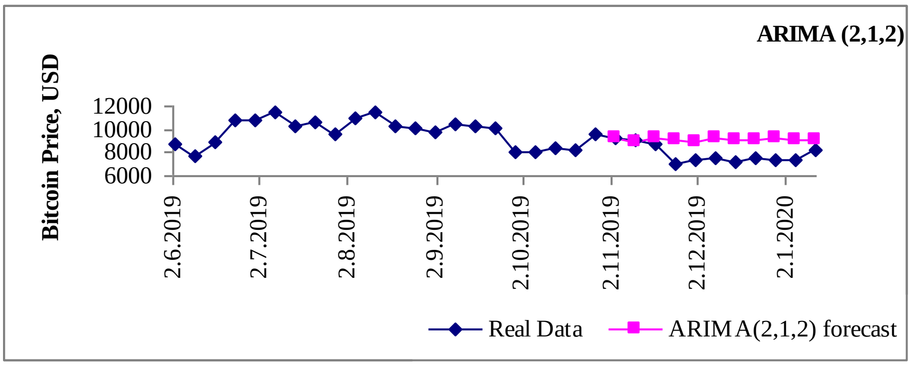

Fig. 4. Forecast from ARIMA (2, 1, 2) for the test set the price of bitcoin

Thus, the constructed ARIMA model (2,1,2) contains two autoregressive parameters and two moving average parameters, which are calculated for a time series after taking the difference with lag 1. Also, the authors obtained the NNAR neural network (7, 7), in which the length of the lag and the number of nodes in the hidden layer are 7.

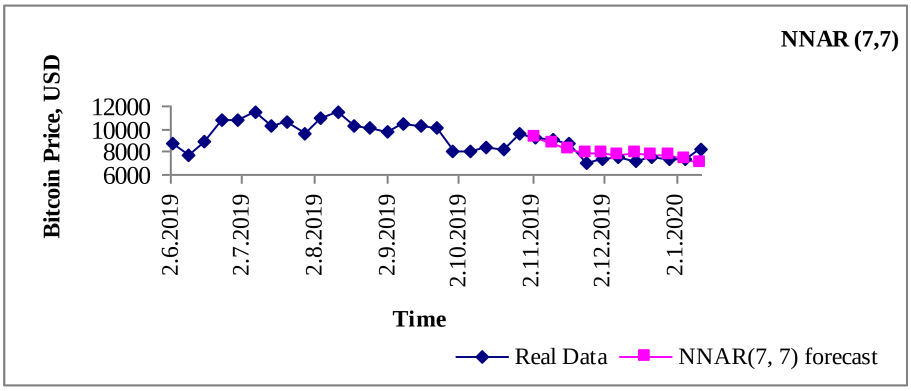

Fig. 5. Forecast from NNAR (7, 7) for the test set the price of bitcoin

Compared the obtained predicted values for the constructed models with real data in the test set. From the graphical representation of the data in fig. 4 and fig. 5 shows that the predicted data of the NNAR model (7, 7) are closer to real ones. From fig. 6 as we can see the obtained forecast data do not go beyond the 95% confidence interval, that is, there is a fairly accurate forecast. This is also evidenced by the value of the mean absolute percentage error (MAPE): for ARIMA it is 18.4%, and for the neural network – 6.1%. Therefore, for medium-term forecasting of the price of bitcoin, it is better to use a neural network NNAR (7, 7), since the forecast will be more accurate.

The results of forecasting the price of bitcoin for the next 10 weeks (January 19, 2020 – March 22, 2020) using the model NNAR (7,7) are presented in fig. 7.
In accordance with the forecast, the price of bitcoin in this period will have a decreasing trend and decrease by 25, 6%, from 8192.49 USD to 6093.467 USD per bitcoin.

For the time series of the "bitcoin" request frequency from Ukrainian online users the best ARIMA model for test data was ARIMA (0, 1, 0). And the best neural model for the time series of requests for bitcoin is the NNAR (8.7) (fig. 8).
Comparing the predicted values for the obtained models with real data in the test sample (fig. 9), we see that they do not go beyond the 95% confidence interval.

The mean absolute percentage error (MAPE) value for the ARIMA model is 9.09%, and for the neural network – 11.7% (table 1). But it should be noted that the ARIMA model (0,1,0) is a random walk model, so the forecast can be made only one period ahead. Therefore, this model can only be used for short-term forecasting. For medium-term forecasting of requests for bitcoin of Ukrainian online users, a neural network model was used, namely, NNAR (8, 7).

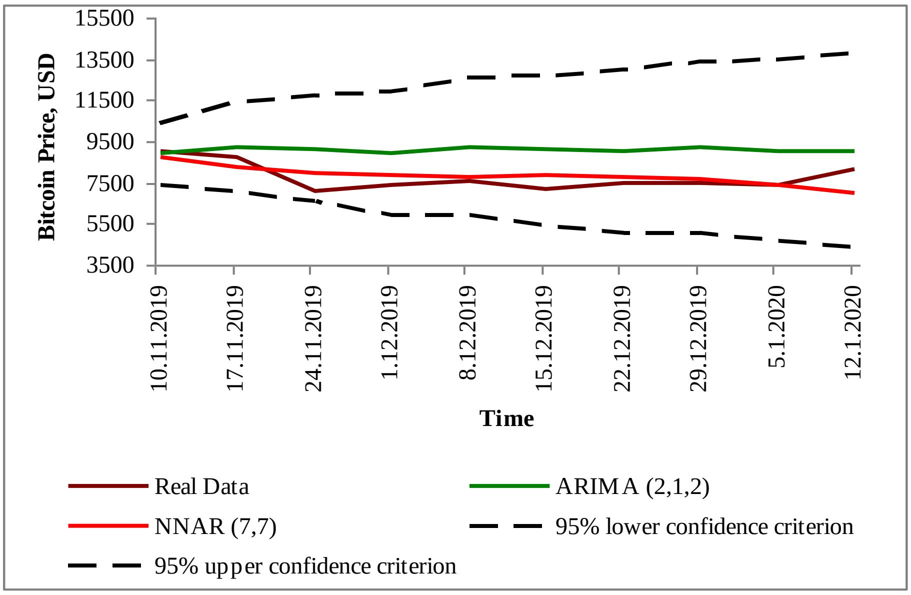

Fig. 6. Forecast for the test set the price of bitcoin

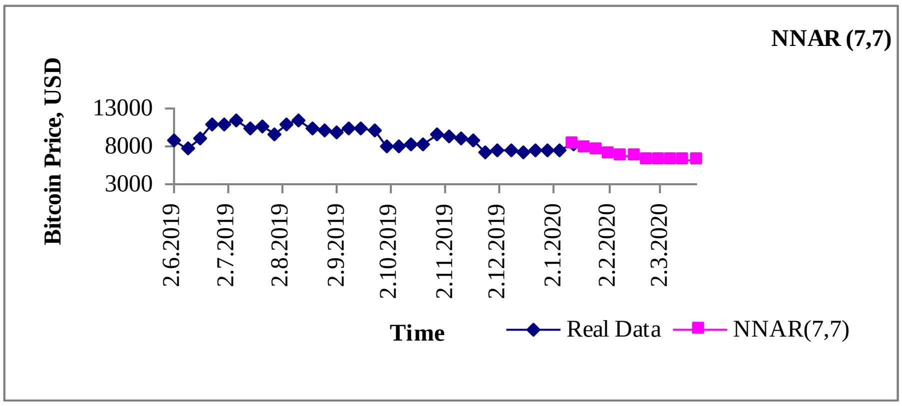

Fig. 7. Forecast from NNAR (7, 7) for the price of bitcoin

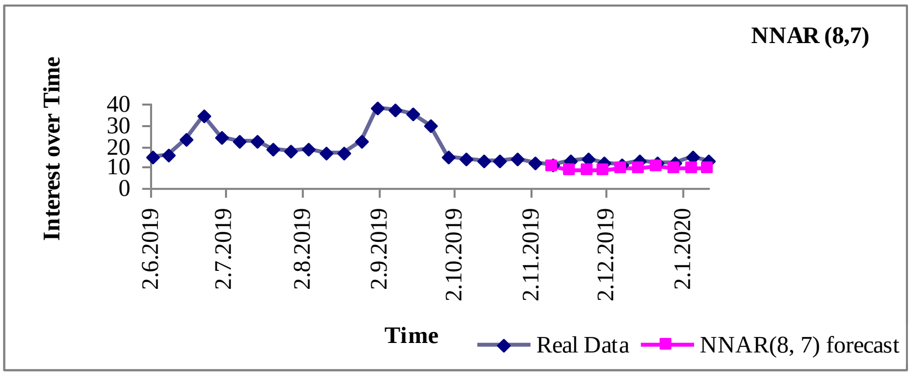

Fig. 8. Forecast from NNAR (8, 7) for the test set the requests "bitcoin"

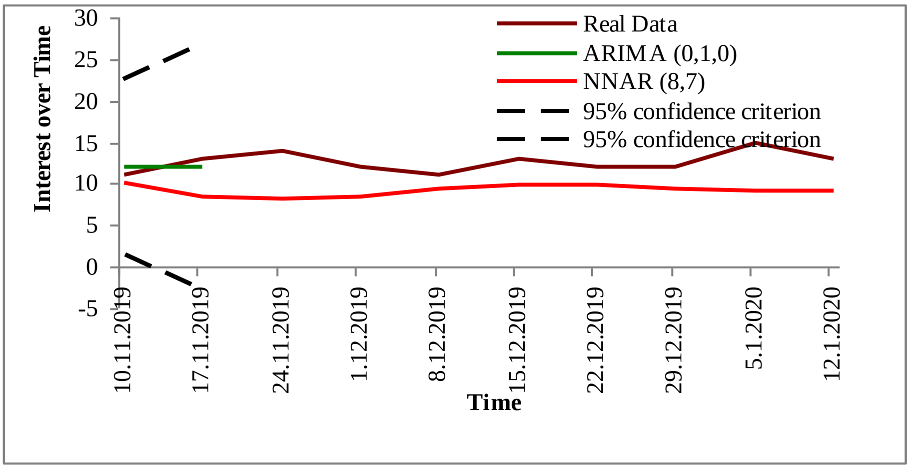

Fig. 9. Forecast for the test set the requests "bitcoin"

Table 1. Comparing forecasting results

Time	Auto-Regressive Integrated Moving Average (ARIMA) model		Neural Network Auto-Regressive (NNAR) model	
	the price of bitcoin	the frequency of requests for bitcoin	the price of bitcoin	the frequency of requests for bitcoin
10.11.2019	8878,67	12	8721,588	10,134
17.11.2019	9227,636	12	8211,657	8,497
24.11.2019	9148,794	12	7962,576	8,135
01.12.2019	8943,138	12	7876,07	8,370
08.12.2019	9230,276	12	7733,796	9,366
15.12.2019	9092,271	12	7823,07	9,749
22.12.2019	9001,815	12	7781,075	9,816
29.12.2019	9214,146	12	7628,991	9,478
05.01.2020	9060,785	12	7344,58	9,218
12.01.2020	9049,155	12	7016,984	9,249

MAPE	18,4%	9,09%	6,1%	11,7%

The results of forecasting the frequency of requests "bitcoin" by Ukrainian online users for the next 10 weeks (January 19, 2020 - March 22, 2020) are presented in table 2.

According to the forecast, the frequency of requests “bitcoin” of Ukrainian online users in this period will increase by 41.7%, from 12 interest over time to 17 interest over time per week. Thus, it is forecasted that the average frequency of requests will increase by 2.4% weekly.

Table 2. The forecast of the studied indicators by the method NNAR

Time	**The price of bitcoin**		**The frequency of requests for bitcoin**	
	$USD	**Rate of increase, %**	**Request frequency**	**Rate of increase, %**
19.01.2020	7627,617	–	13,83168	–
26.01.2020	7421,916	-2,70%	14,71267	6,37%
02.02.2020	7058,429	-4,90%	14,03004	-4,64%
09.02.2020	6631,057	-6,05%	15,26786	8,82%
16.02.2020	6556,085	-1,13%	16,18115	5,98%
23.02.2020	6238,652	-4,84%	15,41361	-4,74%
01.03.2020	6267,147	0,46%	15,93974	3,41%
08.03.2020	6252,667	-0,23%	16,31639	2,36%
15.03.2020	6123,963	-2,06%	16,42473	0,66%
22.03.2020	6093,467	-0,50%	17,04905	3,80%

6 Conclusions

As a result of the research, the importance of taking into account the risks of the methodology for predicting the key parameters of bitcoin, whose nature and mechanism of functioning are distinguished by decentralization, self-organization and the internal complexity of processes increasing in time, is confirmed. The indicated characteristics of an electronic instrument today have shown a limited methodology and variability in the risks of using various methods of forecasting and predicting both the price of bitcoin and the frequency of requests "bitcoin". The studied series of dynamics are defined as integrated time series of the first order, non-stationary, with no seasonal, but with a random component present, which corresponds to the features of the mechanism of functioning of bitcoin. The statistical dependence and interdependence of the series of the dynamics of the price of bitcoin and the frequency of online requests for bitcoin is proved. Interest in bitcoin in the online environment is growing like the dynamics of its course during periods of significant volatility. Whereas during the period of stabilization of the price of bitcoin, uniform periodic monitoring is carried out in the online environment. Certain patterns can be used to explain the trends in bitcoin parameters and the socio-economic behavior of agents in this market sector. The article defines the approach and forecasting procedure for the studied series of dynamics, which essentially correspond to the basic principles of the forecasting methodology and takes into account the specifics and socio-economic content of the price of bitcoin and the frequency of online requests about it. Based on the results of applying forecasting methods to the studied time series of dynamics, it was determined that the processes of self-organization of the bitcoin functioning mechanism provide for the advisability of using forecasting methods with internal procedures for self-learning, self-tuning and adaptation in real time. So, the minimum risks for the study of the bitcoin price time series dynamics were demonstrated by the neural network methodology in comparison with the use of the ARIMA model. Although estimates of forecasting quality using the methods used are generally acceptable, the risk of using the ARIMA model methodology also lies in the fact that its advisability can be limited only to short-term forecasting (for one period), while neural network technology justifies itself in medium-term forecasting tasks. Given the dynamism and daily updating of data on the parameters of bitcoin, in practice it most often manifests itself in short-term forecasting, while for basic research is - medium and long-term forecasting. The authors also note that the results of forecasting the price of bitcoin for the period January 19, 2020 - March 22, 2020 prove the formation of a decreasing trend (-25.6%), while the forecast frequency of requests during this period will increase by 41.7%. Since the authors have proved that an increase in the frequency of requests "bitcoin" corresponds to its high volatility in the direction of increase, it is logical to say that in the forecast period, the dynamics of the price of bitcoin will be characterized by high variability and an increase will take place after a certain decline. Subsequent researchers provide for a recurrency analysis of bitcoin prices and the frequency of online requests "bitcoin", which will complement knowledge about the risks of using separate methodologies for their forecasting, evaluation, and analysis.

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