ORIGINAL SCIENTIFIC PAPER

BITCOIN MONTHLY RETURN FORECAST: A COMPARISON OF ARIMA AND MULTI LAYER PERCEPTRON ARTIFICIAL NEURAL NETWORK

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ABSTRACT

In this paper, we compare the predictive power of Auto Regressive Integrated Moving Averages (ARIMA) and Multi-Layer Perceptron Artificial Neural Networks (MLP ANN) model to short-term forecast the monthly returns of Bitcoin cryptocurrency. We evaluate the performance of two models using time series with monthly data from January 2018 to December 2021. The key parameters for the final assessment of prognostic models are the values of Root Mean Square Error - RMSE and Forecast Error - FE. The results of the short-term BTC return forecast showed better properties of composite compared to univariate time series forecasting models, i.e., higher prognostic power of the MLP ANN model compared to the selected ARIMA (1,1,3) model (lower RMSE and FE). The results point to further comparative research of prognostic models and the possibility of forming more complex and hybrid structures of neural network models in order to predict economic phenomena as accurately as possible.

Keywords: *Bitcoin, Return, Time Series Forecasting, ARIMA, Multi-Layer Perceptron Artificial Neural Networks*

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INTRODUCTION

Cryptocurrency is a form of e-money, i.e., an alternative currency transferable between individuals and therefore represents a digital medium of exchange [1]. Cryptocurrencies must meet several criteria: decentralization, security, speed, reliability, assurance of immediate payment and minimal risk [2]. Considering that cryptocurrencies are still developing and have been partially accepted by the market, none of the cryptocurrencies in use today meet all the requirements, since there are still no common standards [3].

The cryptocurrency that launched the entire system and is today the trademark of the crypto-market is Bitcoin (hereinafter: BTC). During 2008, a text by the author Satoshi Nakamoto was published on Internet, in which BTC is mentioned for the first time and where a completely new type of digital money is briefly described [4]. Since 2009, when BTC trading officially began, until today, the true identity of the creator has not been established. In addition to several people who are suspected of being behind this pseudonym, there is also a suspicion that they are several companies: two Japanese, one Korean and one American - SAMsung, TOSHIba, NAKAmichi and MOTOROLA [5].

Cryptocurrencies are characterized by high volatility, which is particularly pronounced during periods of crisis. The beginning of the Covid-19 pandemic in March 2020 signalled an extreme rise in the values of numerous cryptocurrencies, primarily BTC, whose value rose sharply by more than 700%. In these conditions, digital currencies, in addition to gold, become safe assets and havens not only for institutional and corporate investors, but increasingly for ordinary people who take speculative risks and trade them. Comparing the value movements of the three most important cryptocurrencies today - BTC, Ethereum (hereinafter: ETH) and Ripple (hereinafter: XRP), in the observed period of the pandemic, we notice significant volatility and growth in the value of the cryptocurrency ETH, and in one period at the beginning of 2021, the opposite movements in relation to BTC and XRP (Fig.1.).

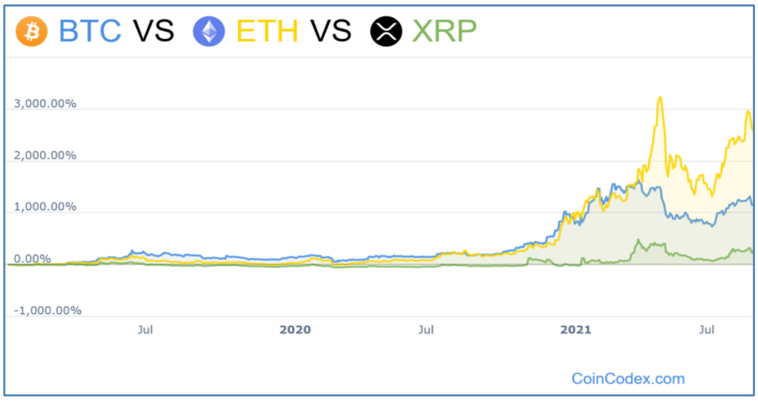

Figure 1. *BTC - ETH - XRP value movements in the period 2020/2021*
Source: [6]

Cryptocurrencies, as global and decentralized, are not under the control of any state and are therefore less sensitive to political events [7]. Nevertheless, a clear upward trend in the price of BTC (as well as other cryptocurrencies) is observed every time there is a political or financial crisis in the world, and even when there is only an indication that a crisis might occur. The price increased during the Cyprus crisis, the Greek crisis, after the BREXIT referendum and the presidential elections in America, as well as during the Covid-19 crisis. So, whenever the trust in the existing system is shaken, a certain number of people in the world obviously see an alternative in cryptocurrencies [8]. It should also be noted that the number of countries in the world that legalize them is growing and that the number of large companies that currently use several cryptocurrencies as a means of payment, as well as the fact that Bitcoin futures contracts have been listed on two exchanges in the USA (CME and CBOE) [9].

In the spirit of the growing interest of the scientific and professional public in understanding new trends in the digital economy and finance, the subject of this paper's research is the short-term prediction of returns on the cryptocurrency market, with a focus on BTC. In this research, a comparison of two forecasting models will be made: ARIMA model as the univariate and Multi-Layer Perceptron artificial neural network (MLP ANN) model as the composite. The research will be conducted on the basis of BTC, ETH and XRP monthly returns data for a four-year period (January 2018 - December 2021). In accordance with the research subject, several goals were set: 1. To compare the performance and forecasting power of two different models for time series forecasting; 2. Determine the prognostic capabilities of the MLP ANN model, and 3. Perform short-term forecasting of future BTC monthly returns.

The paper is structured as follows: the introduction is followed by a review of the relevant literature; in the next section we present the research methodology with a focus on time series and forecasting models - ARIMA and MLP ANN; followed by the results with the discussion and a conclusion with recommendations for further research.

LITERATURE REVIEW

With the advent of cryptocurrencies (digital currencies), the universe of investment assets and possibilities has expanded. Van Wijk [10] states that actual expectations of underlying financial assets can help investors form expectations for investing in BTC. He concludes that most of the assets, which he found to affect the price of BTC, are related to the USA economy. Golez and Koudijs [11] suggest that the predictability of returns on financial assets is of great interest in the financial literature. Empirical evidence suggests that stock returns are indeed partially predictable Using daily and weekly data, within the dynamic conditional correlation (DCC) model, Engle [12] and other authors ([13], [14]) show that BTC can serve as an effective diversifier of the investment portfolio in most cases. Cheah and Fry [15], Katsiampa [16] find that cryptocurrency price volatility is a result of market sentiment, which can be associated with significant "memory". According to these studies, "memory" of cryptocurrency price shocks are semi-important determinants of cryptocurrency prices. Dihrberg [17] finds that BTC can be an ideal tool for risk-averse investors as a buffer against negative market shocks, and then, in her next study, the same author concludes that BTC can serve as a hedge against market-specific risk [18]. Chen [19] concludes the following: a) in the short term, BTC price is positively influenced by its historical values; b) means of exchange and financial expectations have a significant impact on BTC prices, either positive or negative, and; c) the price of BTC, in the short term, is not determined by Blockchain technology. Seiter [20] examines the correlation of the three most important cryptocurrencies (BTC, ETH and XRP) by applying econometric tools to their time series. He compares cryptocurrency returns to six major stock indices: S&P500, Russell 2000, Stoxx 600, Nikkei 225, Hang Seng and S&P Global 1200. The author indicates that the considered cryptocurrencies can be considered a new class of assets, fully digital financial instruments *sui-generis*, as they are not coherently linked to the stock market. However, capital allocation to cryptocurrencies remains in the realm of pure speculation due to their high volatility.

Felizardo *et al.* [21] compare different methodologies such as ARIMA, Random Forest (RF), Support Vector Machine (SVM), Long Short-Term Memory (LSTM) and WaveNets for BTC future price forecasting. They find that the performance of the ARIMA model is weaker compared to the new composite models. Serra [22] concludes that ARIMA models outperform econometric models in explaining cryptocurrency price behaviour, due to smaller values of errors in step-ahead forecasts, but also due to autocorrelation values of residuals in all types of econometric models (weak evidence only for ETH and LTC). Within the selected ARIMA models, the cryptocurrency with the lowest RMSE (0.090) is BTC. Vidyulatha, Mounika and Arpitha [23] present a suitable model that can best predict the BTC market price by applying ARIMA time series analysis. ARIMA is compared with a machine learning algorithm for a linear regression (LR) model. Prediction results showed that the proposed ARIMA model achieved superior performance compared to the LR machine learning model. Emiris, Christoforou and Florakis [24] compared different types of neural networks using the prices of the most traded digital currencies (BTC, ETH and LTC) in classification settings and regressions. They consider Feedforward Networks (FNN) and Recurrent Neural Networks (RNN) along with their enhancements, namely Long Short-Term Memory (LSTM) and Recurrent Blocking Units. The results of the comparative analysis show that RNNs provide the most promising results. Jong-Min, Cho and Jun [25] use linear and non-linear *Error Correction Model (ECM)* to forecast BTC daily returns. Linear ECM is the best BTC prediction model compared to neural network and autoregressive models in terms of RMSE, MAE and MAPE. Using linear ECM and Granger causality tests for fourteen cryptocurrencies, the authors show the causal relationships between BTC and other cryptocurrencies. Nasirtafreshi [26] in his research uses a new deep learning model to predict the price of cryptocurrencies. The proposed model uses a recurrent neural network (RNN) algorithm based on the LSTM method to predict future prices. In the presented simulation results of the proposed method, RMSE, MAE, MAPE, and R^2 are compared with other similar ANNs methods. The author proves the superiority of the RNN method in forecasting compared to other methods. Atlan and Pençe [27] develop an MLP algorithm to predict future BTC prices, using the US Dollar/Turkish Lira exchange rate and BTC values for the database from December 2016 to December 2018. They conclude that the MLP network can be successfully used to predict BTC prices, but also the cryptocurrency ETH and XRP prices. The success of predicting the future prices of BTC, ETH and LTC cryptocurrencies using MLP and LSTM models is confirmed in the study by Jay *et al*. [28]

RESEARCH METHODOLOGY

Time series data

The data on which the research is based are the monthly returns of BTC, ETH and XRP cryptocurrencies for the four-year period - January 2018 - December 2021 (time series of 48 monthly data). Due to the robustness of the data, the logarithmic monthly returns of the above-mentioned variables will be applied in the modelling, using the formula:

$$r = \log \frac{P_t}{P_{t-1}} \tag{1}$$

Where: P_t – closing price at time t (last trading day of the month); P_{t-1} – closing price at time t-1 (first trading day of the month).

Monthly returns (r) are calculated based on daily BTC prices in a given period, taken from *the Yahoo Finance* website [29]. The presentation of the time series of the monthly logarithmic returns of the cryptocurrency BTC is given in Fig. 2.

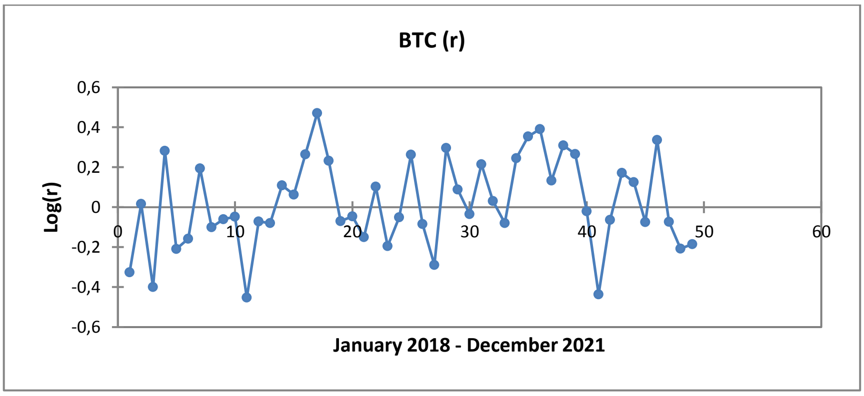

Figure 2. *2018-2021 Time series of the monthly BTC return*
Source: Authors

The time series of the monthly returns of ETH and XRP will be used in the construction of the network of the second model (composite MLP ANN). In forecasting modelling, the most important place is occupied by the analysis of time series, which represents the fundamental basis for all prognostic models. [30] [31] The basic prerequisite for the formation of a successful prognostic model is the *stationarity* of the time series. Several econometric tests are used to assess the stationarity of the time series: Dicky-Fuller (ADF) test and Phillips- Perron test.

FORECASTING METHODS

The goal of all forecasting methods is to predict the future values of the observed phenomenon with as little forecast error as possible. All time series forecasting methods are classified into three groups: qualitative, quantitative and composite (combined) [32] [33]. Quantitative prognostic models are dominated by multi-linear regression econometric models with their variants, exponential alignment and autoregressive models (ARMA, ARIMA). These models belong to univariate forecasting models.

Composite or combined (multivariate) forecasting models represent a combination of several methods, predominantly quantitative, where most authors highlight their prognostic power and much smaller forecast error. The most famous models from this group are vector autoregressive models (VAR), Bayesian forecast model, neural network models (e.g., ANNs, NNAR). Based on numerous empirical comparisons of different models for predicting economic phenomena, Lovrić, Milanović and Stamenković [33] support the opinion of Armstrong [34]:

- Combined forecasting models give better forecasting results than univariate ARIMA models;
- The best results are given by index prediction methods and neural network models.

The general methodology of modelling the ARIMA process was conceived by George Box and Gwilym Jenkins in 1970, so it is called the Box-Jenkins methodology after them. The basis of this methodology consists of three stages (phases) of developing a time series model: 1. Model identification; 2. Evaluation of the model, 3. Model adequacy check [35] [36] [37].

Model identification This phase implies the procedure of using the data of the basic time series (at the level) in order to extract a narrower class of ARIMA models. Based on time series graphics, ordinary (ACF) and partial (PACF) correlograms, it is determined whether it is necessary to transform the series beforehand in order to stabilize the variance and achieve stationarity [30] [38]. For this purpose, logarithmic transformation and differentiation are most often used. As economic series are usually characterized by marked non-stationarity, difference application procedures are almost always present in time series modelling. After the performed transformation, and checking the stationarity of the series through the ADF test, it is possible to choose the appropriate class of AR, MA or ARMA models, where the evaluation of the model is carried out [30] [39] [40].

Evaluation of the model. The key parameters for the assessment are: adjusted coefficient of determination - adj. R^2, Root Mean Square Error – RMSE, Mean Absolute Percentage Error – MAPE, Mean Absolute Error - MAE, Bayesian Information Criterion – BIC/ SBIC and modified Box-Pierce autocorrelation statistics i.e., Ljung-Box Q [36] [37] [41] [42].

Acceptable values of the specified parameters that indicate that the model is adequate for prediction are shown in Table 1.

Table 1. *Values of model parameters that indicate the adequacy of the model for prediction*

Parameter	Tends to / Critical value
RMSE	Minimum
MAPE	Minimum
MAE	Minimum
SBIC	Minimum
Ljung-Box Q	$\chi2(18; 0,05) = 28,869$ Ljung-Box Q* < $\chi2(DF; 0,05)$

Source: Authors

Model adequacy check. The goal is to identify possible shortcomings of the model. The basic steps include checking the statistical significance of the evaluated coefficients and checking the assumption that the residuals of the evaluated model represent *a white noise* process, i.e., it is necessary that the residuals meet the conditions of normal distribution and absence of autocorrelation. If it turns out that there are no defects, the model can be used to make predictions. Otherwise, improvement is possible, so the ARIMA model building process continues - re-specification, evaluation and verification of model adequacy. The critical values of the autocorrelation functions (ACF and PACF) in our research are obtained using the form:

$$\pm 1{,}96\sqrt{\frac{1}{n}} = \pm 1{,}96\sqrt{\frac{1}{48}} = 0{,}282 \qquad (2)$$

Where *n* is the number of observations.

Susruth [43] and Banga [44] emphasize the necessity of calculating the real forecast error (*Forecast Error - FE*). FE is obtained as follows:

$$FE = \frac{ACTUAL\ VALUE - FORECAST\ VALUE}{ACTUAL\ VALUE} \quad (3)$$

Neural networks (Neural Networks) are programs or hardware assemblies that, usually through an iterative process from past data, try to find a connection between the input and output variables of the model, in order to obtain the output value for the new input variables [45]. An artificial neuron is a unit for processing data (variables) that receives weighted input values from other variables, transforms the received value according to some formula and sends the output to other variables. Learning takes place by changing the values of the "weights" among the variables (the weights w_i - are the weights by which the input values in a "neuron" are multiplied). The network function can be represented as:

$$y_i = f\left(\sum_j w_{ij}\, y_j\right) \quad (4)$$

Where: y_i – output neuron; y_j – input neuron; w_i – weights of input neurons.

One of the most commonly used neural network algorithms is the *Multi-Layer Perceptron (MLP).* A "multilayer perceptron" network is a "*feed forward*" network, in which the layers of the network are connected in such a way that signals travel in only one direction, from the inputs to the outputs of the network. The best-known and most frequently used algorithm applied for learning and training multi-layer perceptron networks is the so-called "*backpropagation*" network. The "backpropagation" network algorithm was crucial for the widespread commercial use of this methodology, making neural networks a widely used and popular method in various fields. The standard "backpropagation" network algorithm involves error optimization using a deterministic gradient descent algorithm. The structure of the network consists of an input layer, an output layer and at least one hidden layer with a forward link [45] [46].

The neural network architecture consists of at least three layers, and the number of units (neurons) in the hidden layer and the learning distance are obtained by the cross-validation process. The learning (training) of the network takes place on the training sample (usually 60-80% of the total sample), and each combination is tested on the validation sample (10-20% of the total sample). The goal is to find the learning distance and network structure that give the best result on the validation sample. Finally, the network thus obtained is tested on the test sample (20% of the total sample), and the obtained RMSE results after the testing phase are the final measure of the success of the network. The most common output functions are the Sigmoid (S) and Tangent hyperbolic function (Tanh), while the Delta rule with a momentum of 0.7 and a dynamic learning coefficient of 0.1 to 0.9 is used as a learning rule. Mean Square Error (MSE) or Root Mean Square Error (RMSE) are most often used to calculate the error of a neural network.

For the formation of the MLP neural network in this case, two inputs were chosen, i.e., two variables – the monthly returns of the cryptocurrencies ETH and XRP, based on the regression results for the dependent variable BTC(r). In the following, we present the steps of selecting an MLP neural network for predicting BTC(r) monthly returns, with two input, one hidden and one output layer. The steps are as follows:

(1) Checking the stationarity of the time series BTC(r), ETH(r), XRP(r) - at the level, applying the first difference in the transformation, checking the stationarity by means of the extended Dickey-Fuller test ADF; (2) MLP ANN network setup 1: Sigmoid of f, variable normalization (0.1), network architecture 80:20, hidden layers 1, momentum 0.7; epoch 1000; (3) Setup of MLP ANN network 2 – Tanh of f; normalization of variables (-1,1); (4) Evaluation of network performance: RMSE:

$$RMSE = \sqrt{\frac{SSE}{N}} = \sqrt{\frac{\sum (e_t)^2}{N}} \quad (5)$$

Where: e_t – is the individual error of the variable; N – number of variables/errors; SSE – Sum of Squared Error

(5) Selection of MLP NN network for predicting BTC(r); (6) Evaluation of network performance in training (learning) and testing - RMSE.

RESULTS AND DISCUSSION

ARIMA model results

Since the ACF, PACF and ADF test showed the non-stationarity of the BTC(r) time series in the first step, in order to reduce the series to stationary, it is necessary to differentiate the series. The layout of the differentiated series (first difference) is shown in Fig. 3.

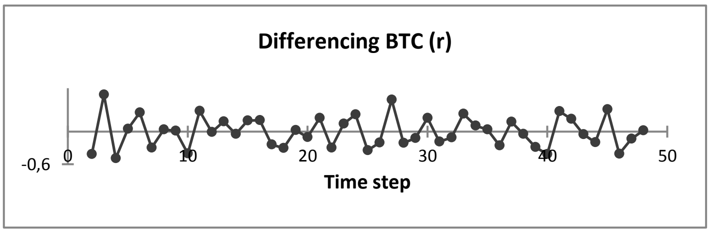

Figure 3. *Differentiated BTC(r) time series*
Source: Authors

After differentiating the BTC(r) return time series on the first differentiator, the stationarity of the series was achieved. ADF test and Phillips-Perron test show the achieved stationarity (Table 3).

Table 3. *Unit root tests of the differentiated series DiffBTC(r) (ADF, PP)*

	Dickey-Fuller test (ADF)	Phillips-Perron test
Tau (Observed value)	-3.962	-12.254
Tau (Critical value)	-0.681	-1.948
p-value (one-tailed)	**0.016**	**< 0.0001**
alpha	0.05	0.05

Source: Authors

ADF and Phillips-Perron Tests interpretation: H0: There is a unit root for the series; **Ha: There is no unit root for the series. The series is stationary.** As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.

In the second step, we analyse the correlograms of the autocorrelation function (ACF) and the partial function (PACF) with threshold values of +/- 0.282, based on which the type of AR and MA process is determined. From Fig. 4 it is clearly visible that in this case it is AR (1) and MA (3) processes. Given that we have the time series stationary on the first difference, we finally get the forecast model ARIMA (1,1,3) for DiffBTC(r). The results of fit statistics of the obtained model are shown in Table 4.

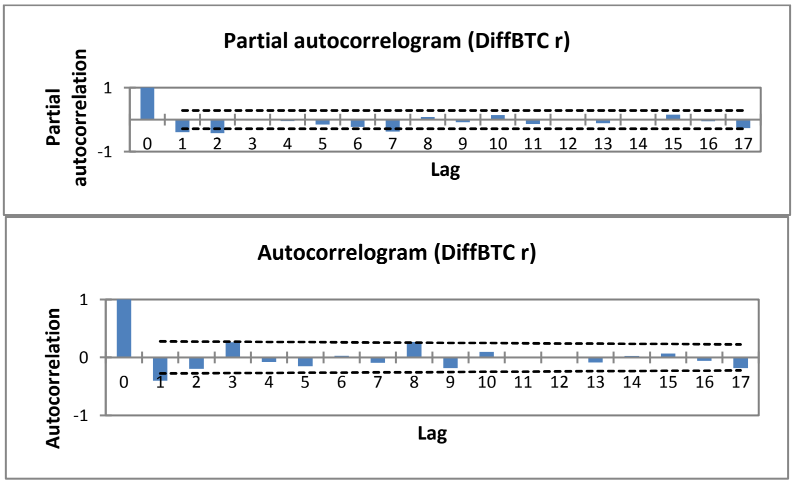

Figure 4. *ACF and PACF correlograms of the differentiated series DiffBTC(r)*
Source: Authors

Table 4. *Performance of the DiffBTC(r)ARIMA(1,1,3) model*

R^2	MSE	RMSE	MAPE	SBIC	Ljung-Box Q	FE
0.696	0.077	**0.279**	196.843	-2.145	χ2(14; 0.05) = 23.685 14.490 < χ2(14; 0.05)	**0.30**

Source: Authors

In order to test the existence of autocorrelation of the fitted model, the so-called Portmanteau test i.e., Ljung-Box Q test of autocorrelation of residuals is used. It starts from the hypothesis H0: The autocorrelation values on the group of lags of the residuals of the time series model are not significantly different from zero or otherwise H0: The model is adequate for forecasting. It is necessary that the obtained statistic value is: Q < χ2(DF, p) = Null Hypothesis will be accepted. We see that the obtained values of the Q statistic are less than the threshold table value for the degrees of freedom of 14 and the significance level of p=0.05, so we accept H0 and conclude that the model is adequate for prediction. The obtained values of RMSE = 0.279, Bayesian (Schwartz) Information Criterion – SBIC = - 2.145 and realistic prediction errors – FE = - 0.93 will be of crucial importance to us in comparison with other prognostic models. Fig. 5. shows the forecast values of BTC monthly returns for the period from January 2022 to December 2022.

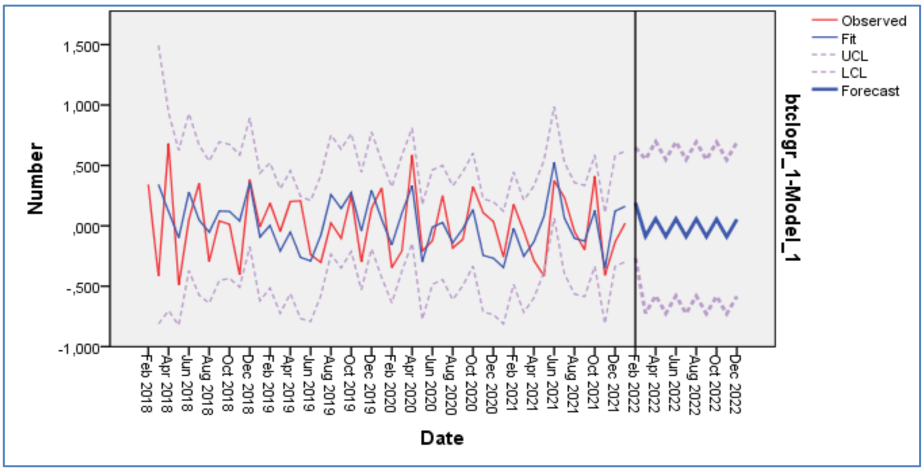

Figure 5. *Graphic representation of forecasting monthly BTC returns via ARIMA model*

Source: Authors

MULTI-LAYER PERCEPTRON MODEL RESULTS

The neural network MLP ANN is formed with two input variables (neurons) – monthly returns of cryptocurrencies ETH(r) and XRP(r) and one output BTC(r). These cryptocurrencies were selected based on numerous findings on statistically significant determinants of monthly BTC price and return movements. Before forming the MLP ANN network, the stationarity of the input variables was established. The input variable XRP(r) is needed to be logarithmically transformed to achieve stationarity. Target output variable BTC(r) remained at the first differential. MLP ANN networks with two activation functions were considered: Sigmoid (S) and Tangent-Hyperbolic (Tanh), with one hidden layer (Hidden Layer) and 80-20 network training and testing setup. For each of the networks, 10 simulations were performed and the sums of squared errors (SE) of the network were recorded in the phase of learning and testing the network. The network with the lowest values of MSE and standard deviation was selected. In this case, the ANN6 network with the activation Sigmoid function showed the best performance. The aforementioned is shown in Table 5.

Table 5. *Values of MLP ANN 1-2 by ten (10) simulations (one hidden layer)*

BTC(r) MLP ANN	*MLP ANN1 Sigmoid (S)*		*MLP ANN2 Tangent –Hyperbolic (Tanh)*	
	Hidden Layer 1 80%-20%		*Hidden Layer 1 80%-20%*	
	Training	*Testing*	*Training*	*Testing*
ANN1	0.673795221	0.286356421	1.240698728	0.560059521
ANN2	0.629550104	0.275680975	1.259894175	0.742518238
ANN3	0.654980916	0.357770876	1.228277927	0.623965811
ANN4	0.615900425	0.303315018	1.29305839	0.476095229
ANN5	0.646013416	0.361939221	1.213534782	0.562435181
ANN6	**0.632982359**	**0.266458252**	1.330162897	0.693541635
ANM7	0.735753582	0.503322296	1.301153335	0.393700394
ANN8	0.634297512	0.393700394	1.287762918	0.554677083
ANN9	0.598887858	0.359629439	1.370523015	0.486826458
ANN10	0.596098426	0.347371079	1.301153335	0.410690476
MSE	**0.641825982**	**0.345554397**	1.28262195	0.550451003
Stand.Dev.	**0.038636025**	**0.066524371**	0.045617245	0.108029443

Source: Authors

The architecture of the selected MLP ANN prediction network and the results of the network are shown in Fig.6. and Tables 6 and 7.

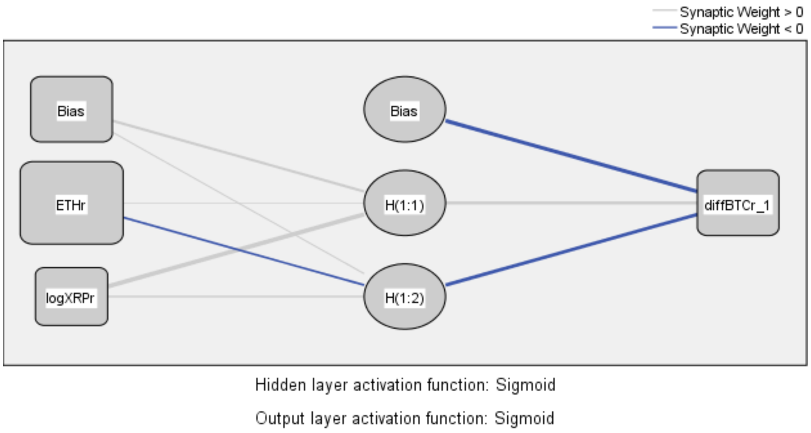

Figure 6. *Architecture of the selected MLP ANN*

Table 6. *MLP ANN error results*

Model Summary

Training	Sum of Squares Error	**1.293**
	Relative Error	**1.010**
	Stopping Rule Used	**1 consecutive step(s) with no decrease in error[a]**
	Training Time	**0:00:00.01**
Testing	Sum of Squares Error	**,250**
	Relative Error	**1.026**

Dependent Variable: DIFF(BTCr,1)

Table 7. *MLP ANN parameter estimates and independent variable importance*

Parameter Estimates

Predictor		Predicted		
		Hidden Layer 1		Output Layer
		H(1:1)	H(1:2)	diffBTCr_1
Input Layer	(Bias)	**,286**	**,157**	
	ETHr	**,117**	**-,273**	
	logXRPr	**,475**	**,271**	
Hidden Layer 1	(Bias)			**-,436**
	H(1:1)			**,314**
	H(1:2)			**-,385**

Independent Variable Importance

	Importance	Normalized Importance
ETHr	**,779**	**100,0%**
logXRPr	**,221**	**28,4%**

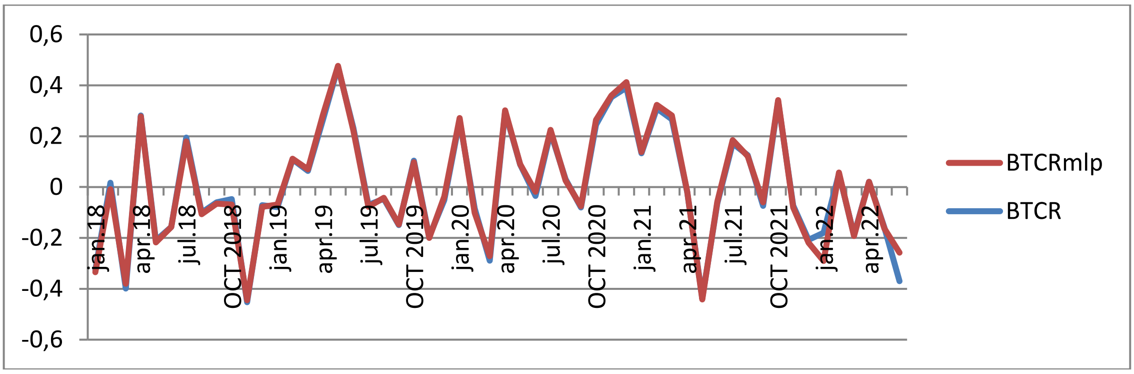

Figure 7. *Display of actual and forecast values of BTC returns via MLP ANN*
Source: Authors

Table 8. *Performance of ARIMA and MLP ANN models for the forecast period January 2022 - June 2022.*

Month	Actual return	Forecast ARIMA	FE ARIMA	Forecast MLP ANN	FE MLP ANN
January 2022	-0.18	-0.084	0.533	-0.11	0.338
February 2022	0.052	0.191	-2.673	0.0058	-0.25
Mart 2022	-0.188	- 0.086	0.542	-0.0044	-0.175
April 2022	0.021	0.059	-1.809	-0.0005	0.0476
May 2022	-0.16	- 0.088	0.45	-0.0039	0.4375
June 2022	-0.37	0.058	1.156	0.112	0.727
		Mean FE ARIMA:			**0.30**
		MSE ARIMA:			**0.077**
		RMSE ARIMA:			**0.279**
		Mean FE MLP ANN:			**0.187**
		MSE MLP ANN:			**0.004**
		RMSE MLP ANN:			**0.069**

Source: Authors

The results in Table 8 show that the MLP ANN model predicts future monthly BTC returns with a significantly lower root mean square error (RMSE) (0.069) and a lower mean real FE prediction error (0.187) compared to the ARIMA model. Once again, ANNs models have been shown to have much better performance and greater prognostic power than univariate ARIMA time series models. The presentation of the mentioned basic models with the obtained results opens up possibilities for further research, primarily for testing other types of ANNs in order to forecast, with different activation functions, more inputs and outputs and network settings in training and learning.

CONCLUSION

The research aimed to understand the behaviour of the most important cryptocurrency today – BTC. Two different models were used to predict BTC monthly returns - the first, a univariate ARIMA time series prediction model, and the second, a composite Multi-Layer Perceptron (MLP ANN) artificial neural network model, with two input and one output layer. Based on monthly yield data for the period January 2018 - December 2020, a short-term three-month BTC yield forecast is presented. The results showed that the prediction effect of the MLP ANN network is more significant and accurate compared to the identified ARIMA (1,1,3) model, based on the RMSE and FE values. The obtained results are in accordance with numerous literature that showed that ANNs models provide greater accuracy in predicting the behaviour of economic phenomena (prices and returns of stocks, commodity prices...) in relation to ARIMA models [47] [48] [49].

Considering that more and more attention is being paid to cryptocurrencies in recent times, of which there are currently over 12.000, this study can be important for individual and institutional investors as it can help them better understand the behaviour of prices and returns of cryptocurrencies, and to some extent reduce the risk of investing and trading in the crypto market. Using time series forecasting techniques as well as new artificial intelligence models, investors can primarily reduce the price risk associated with their business operations in the cryptocurrency market, caused by high volatility. Further, the existence of an irregular component should be mentioned, i.e., sudden events (crisis, wars, etc.) which can affect price behaviour. In the case of cryptocurrencies, we have seen that the price volatility of key cryptocurrencies has been slightly impacted by the COVID-19 crisis [50]. The current Russian-Ukrainian war also does not significantly affect the occurrence of extreme cryptocurrency volatility and liquidity decline [51] [52] [53].

For future research, it will be significant to look at the behaviour and measure the performance of some other significant cryptocurrencies with high market capitalization, such as Ethereum, Ripple, Litecoin, Dash... It will be important to look at the results of applying other time series forecasting techniques (e.g., Exponential Smoothing, BVAR, VEC, LVARMA) as well as other types and hybrid models of ANNs, which, according to previous research, have superior performance compared to all other prognostic models.

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