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A new grey system approach to forecast closing price of Bitcoin, Bionic, Cardano, Dogecoin, Ethereum, XRP Cryptocurrencies

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Abstract
The current study uses the grey forecasting model, EGM (1, 1, α, θ), a generalized form of the classical, even form of grey forecasting approach, to forecast the closing price of Bitcoin (BTC), Bionic (BNC), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), XRP (XRP) of cryptocurrencies based on the data from September 19, 2021, to September 29, 2021. The forecast was generated for September 30, 2021–October 07, 2021. Study revealed that the generalized model's forecast accuracy is generally better than that of the classical model. The results are also compared with Linear Regression and Exponential Regression. This superiority results from using real past data in long-term forecasting, while the iterative forecasting approach uses the predicted values. Since forecast values are important in guiding future investments, decision-makers must consider various forecasting methods and select the best forecast performance after analyzing the comparative performance.

Keywords Grey system theory · Cryptocurrencies · Prediction · Time-series

JEL Classification G1 · C18 · C22 · E52

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1 Introduction

Cryptocurrency is a decentralized digital currency (De Vries 2018) which incorporates innovative technologies like blockchain, cryptography, and smart contracts (Xu et al. 2019) to create digital property(Qin et al. 2021). Cryptocurrencies are created and managed by non-governmental agencies (Kim 2015), so it cannot be used to substitute the legal currency (Nakamoto 2008). Franco (2014) considered them as a new opportunity in compare to the traditional fnancial system due to its decentralised structure without any regulated activity. So it mostly used for speculation (Zhang et al. 2021). The transactions with cryptocurrencies are considered secured, fast, convenient, less costly as third-party involvement is not required and their globality(Koblitz and Menezes 2016). The transaction carried out with cryptocurrencies between users are direct and largely anonymous (Miers et al. 2013). Due to this cryptocurrency network has fascinated investors, business entities, and establishments while expediting services and product deals (Faghih Mohammadi Jalali and Heidari 2020).

Cryptocurrencies like Bitcoin have been gradually considered as an investment opportunity due to its ability to hedge or evade risks (Chan et al. 2019) arising out of uncertainities in the global economic condition (Qin, Su and Tao 2021), which resulted in the boom (Chen et al. 2020). Recently, cryptocurrencies have exhibited highly explosive behaviours (rapid price accelerations followed by drastic drops), which have made the investment very risky (Agosto and Cafferata 2020). Lam et al. (2018) fears another financial crisis in the near future to be caused by the cryptocurrency boom, and a major Bitcoin (BTC) price crash triggered by a cyber-hack and a government crackdown (Robert 2017).

Because of its highly volatile nature, it is necessary to understand the ever-changing market environment and develop a good prediction system to base investment decisions (Mikhaylov 2020). Many researchers consider the cryptocurrency market as inefficient (Caporale et al. 2018), and therefore investors try to know the accuracy of these currencies' price prediction methods (Munim et al. 2019). In one hand, the sudden increase in the price of the cryptocurrencies has created new investment opportunities in the area of unconventional currency, but on the other hand its' volatile nature prevents new investment. Due to its highly volatile nature there is an urgent need for a dependable and accurate prediction upon which such investment decision can be based (Chen et al. 2020). So the current study is an honest attempt to fulfill the requirement of a good prediction method created due to price volatility of cryptocurrencies by means of more sophisticated tools and techniques.

Predicting the price of cryptocurrencies is very tricky as the basic nature of these currencies is different from others. It exhibits the attributes of both commodity and fiat money (Selgin 2015). It shows the boom-bust pattern due to its speculative nature, and the majority of investors are hypothetical and short-term oriented (Salisu et al. 2019). So predicting the price of cryptocurrencies using the traditional method based on past trends is not a wise decision.

Many existing studies have used different techniques for better prediction of the prices, like different statistical techniques or have applied different modelling techniques on different samples, and some have applied machine learning for more accurate Bitcoin price prediction (Chen et al. 2020). Researchers have also used modern prediction methods and sophisticated artificial intelligence based on complex machine learning models, often reinforced by deep learning (Hassani et al. 2018). The current study is an attempt to forecast the price of six cryptocurrencies: Bitcoin (BTC), Bionic (BNC), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), XRP (XRP) through a novel grey forecasting model, EGM(1, 1, α, θ), which generalized the classical model EGM (1, 1).

Investors in order to hedge the risks of tradition financial systems are in search of more accurate and better techniques for price prediction.The outcome of the current study will be helpful to such investor as their investment decisions will be based on improved techniques. The new technique with higher degree of accuracy can enhance the confidence level of the investors and can increase the attractiveness of cryptocurrencies as an investment option. The academician can too be benefitted from the result as the new technique being used for the expected result can open new avenues for research. This will encourage and start debates related to the area of study and may lead to the expansion of scope.

2 Literature review

Most of the earlier studies covered concepts, principles, and economics (Dwyer 2015; Becker et al. 2011) associated with cryptocurrencies. They covered origin of cryptocurrency, the supply and demand of digital currencies, market equilibrium, their uses in exchange for goods and services with other rival currencies like the United States Dollar (USD). Bitcoin was the first cryptocurrency to become popular, which was founded in 2008 by Satoshi Nakamoto(García-Corral et al. 2022) which existed in the global market (Garcia 2014).

Umar et al. (2021) consider BTC as an "exclusive marvel of the Fourth Industrial Revolution", and presented cryptocurrencies as the most erudite technological and financial products. Bitcoin (BTC), Bionic (BNC), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), XRP (XRP), etc., are the leading cryptocurrencies that are gaining everywhere and have been better explained as a "means of exchange" (the European Central Bank 2012) and a "unit of value" accepted by a virtual community(García-Corral et al. 2022). At present Bitcoin is the most cherished and pivot of cryptocurrency studies (Jang and Lee 2018). The market capitalization of Bitcoin was USD783 (as of August 01, 2021), up from USD237 billion (as of March 30, 2018) and establishes BTC, as the leader and dominating entity in this area. However, in a long period, the demand for a few other cryptocurrencies competing with BTC (the early industry leader) increased quickly than BTC but later BTC appreciates against the USD, while other currencies depreciate against the USD (Gandal and Halaburda 2016).

In this period, data are consistent with strong network effects, and the winner takes all the dynamics. So this recent explosive pricing trend of cryptocurrencies has attracted the attention of investors and researchers to find more efficient ways for predicting the price to maximize the benefits. Many studies have been carried out to address the serious problems of accurately predicting the price as required by the investors, each using different methodology and the search is still on. Studies have been carried out to identify the best price prediction method in the last few years. Several modifications adopted for increasing accuracy levels were observed and each study claims success at its own merit.Some of these studies were included in the literature review to comprehend the research back ground.

Impressed with the growing trend of cryptocurrencies and lack of comprehensive study in the area, (ElBahrawy et al. 2017) conducted a study about the history of the entire market. It analyzed the behaviour of 1469 cryptocurrencies, introduced between April 2013 and May 2017. The objective was to understand the properties of the cryptocurrency market. After this,a study by Aste (2019) was carried out to identify the dependency and causality structure of the cryptocurrency market. It tried to examine the combined activities of both prices and social sentiment associated with two thousand cryptocurrencies and found that there is a complex and rich arrangement of interrelations where prices and sentiment impact each other, both instantaneously and with lead-lag causal relations. The traditional autoregressive integrated moving average (ARIMA) model is still considered a useful tool for predicting the future value of cryptocurrencies. Some researchers used it to analyze the price time series for three years. It was found that this simple method is efficient for a short period during which the behaviour of the time series does not change (at least for one day) but is not effective for a long period (say three years). For a more accurate price prediction, additional features were to be extracted and used along with the price (Azari 2019).

Munim et al. (2019) have analyzed forecasting of BTC price using the ARIMA and neural network autoregression (NNAR) models. They employed the static forecast approach and forecasted next-day Bitcoin prices both with and without re-estimation of the forecast model for each step. ARIMA beats NNAR in the two test-sample forecast periods with model re-estimation at each step. The Diebold Mariano test approves the supremacy of forecast results of the ARIMA model over NNAR in the test-sample periods. ARIMA performed better in the case of high volatility. The suggestion was to attempt the Recurrent Neural Network(RNN) approach for the price of cryptocurrencies and to use time series models for smart prediction. To improve further, Nguyen et al. (2019) suggested that the system should include a series of processes, e.g., extracting sales data from a website preprocessing raw data, and using an ARIMA model. For evaluating the accuracy of the prediction, RMSE and MAPE performance metrics were used.

To help the traders participating in "day-trading", trading BTC against the US dollar in a concise timeframe for making profits from small market fluctuations, Ibrahim et al. (2021) developed a model. The model can predict price movement's direction for the next 5-min time frame. Several machine learning models were used for this purpose. The tested models include ARIMA, Prophet (by Facebook), Random Forest etc.

Chen et al. (2020) analyzed and predicted BTC prices in two ways based on empirical analysis and robust machine learning algorithms as it have been used to mark precise predictions in many areas, like manufacturing and finance. Due to the lack of seasonality, machine learning models are applicable and useful in predicting the price of cryptocurrencies. So they advocated a method that can accurately use machine learning algorithms to predict BTC prices. To understand the behaviour of price, multifractal behaviour of daily price and volume changes of fifty cryptocurrencies using the MultiFractal Detrended Fluctuation Analysis (MF-DFA) was done by (Stosic et al. 2019).

To know about the nature of digital currencies, some studies examined interdependencies between different cryptocurrencies in the short and long run (Ciaian et al. 2018). From a risk management perspective, a study was carried out to investigate the co-explosivity in the crypto-assets, whether explosivity in one cryptocurrency indication the explosivity in other cryptocurrencies and considered possible shock propagation channels to improve the prediction of market collapses (Agosto and Cafferata 2020). This finding makes the price prediction process more complex.

Begušić et al. (2018) considered that there exists a power-law correlation between price and volume. Uncovering power-law behaviour and studies of scaling exponents unearth the features of complexity in many real-world phenomena like the volatile characteristics of the financial market. Shu and Zhu (2020) applied the log-periodic power law singularity (LPPLS) confidence indicator as a diagnostic tool for identifying bubbles using the daily data on Bitcoin price in the past two years. Further, considering the multi-parametric characteristics of cryptocurrencies, comparative study of the various parameters affecting cryptocurrencies price prediction was done based on deep learning models like Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and Gated Recurrent Unit (GRU) (Aggarwal et al. 2019).

Looking into the characteristics and price performance many researchers used machine learning methods and it was observed that Deep neural network (DNN) based models performed the best for price ups and downs prediction, and LSTM-based prediction models slightly outperformed the other prediction models for BTC price (Ji et al. 2019). Researchers have also used machine learning models including Random Forest, XGBoost, Quadratic Discriminant Analysis, Support Vector Machine, and Long Short-term Memory for Bitcoin 5-min interval price prediction, and results have been compared with traditional statistical forecasting methods. It was found that these are superior to statistical methods, with accuracy reaching 67.2% (Chen et al. 2020), and Dutta et al. (2020) have also shown the same result. Long short-term memory (LSTM) networks with two variant LSTM models (conventional LSTM model and LSTM with AR2 model) were used for predicting the price of BTC, and the study (Wu et al. 2018) confirmed that LSTM with AR(2) model outperformed the conventional LSTM model.

Reflecting on the complex nature of cryptocurrencies, some researchers considered the nature of cryptocurrencies price series as a multi-scale problem and observed the same by investigating its compositional characteristics. They used complete empirical ensemble mode decomposition (CEEMD) on daily BTC prices from 2012 to 2018 to recognize the short-term, medium-term, and long-term movement in the BTC price series. The study used a support vector machine (SVM) learning algorithm to discover its ability to predict BTC prices (D. Aggarwal et al. 2020). Mudassir et al. (2020) emphasized the non-stationary behaviour of BTC prices as data changes over time and employed high-performance machine learning-based classification and regression models to predict BTC price movements and prices in short and medium terms one, seven, thirty, and ninety days. The researchers claimed the superiority of the method in comparison to the existing models.

For better prediction of price study, Atsalakis et al. (2019) used a computational intelligence technique that uses a hybrid Neuro-Fuzzy controller, namely PATSOS, to forecast the direction in the change of the daily price of cryptocurrencies. This methodology outperformed two other computational intelligence models: a more straightforward neuro-fuzzy approach and artificial neural networks. The performance of PATSOS was found to be very robust in the case of other cryptocurrencies (Atsalakis et al. 2019). In their quest to identify the best forecasting method, Deb et al. (2017) focussed on two approaches for forecasting; data-driven forecasting and deterministic forecasting. Grey forecasting model belongs to this category and can use even small data to predict future patterns.

Faghih Mohammadi Jalali and Heidari (2020) used the Grey system theory, a machine learning- approach of forecasting nonlinear time series, to predict the price of BTC and changes associated with it. In the study, they used the first-order grey model GM (1, 1). Most researchers use GM (1, 1) because of the model's simplicity, easy implementation, and low need for time data. The study's outcome demonstrated that the GM (1, 1) model predicts BTC's price precisely and that one can receive a maximum profit confidence level of 98% (approx) by selecting the appropriate time frame and managing investment assets. The average error was as low as 1.14% in a five-day window, which is less than other cited methods. The study also suggested that researchers consider some dependent factors in BTC price and apply GM (1, N) to predict Bitcoin price to get a more extended period prediction. The Grey System prediction model has also been used in various other essential studies: Javed and Liu (2018b) used two grey forecasting models for growth analysis of research publications. Grey Absolute Decision Analysis (GADA) approach was proposed by (Javed et al. 2020a, b, c). (Javed et al. 2020a, b, c) have applied the grey system approach to predict the critical indicators of China's inbound and outbound tourism. To evaluate the agriculture sector's low carbon and sustainable technologies, Islam (2021) used the Grey Ordinal Priority Approach (OPA-G), a modern multi-attribute decision-making technique. (Javed and Liu 2018a) evaluated the association between outpatient satisfaction and several healthcare projects' service quality in Pakistan with the help of Deng's grey incidence analysis (GIA) model. (Javed and Liu 2019) upgraded the existing absolute grey relational analysis (Absolute GRA) model. (Thio 2021) has analyzed Site Selection Criteria for Marine Cultivation in the North Lombok Regency of Indonesia using the Grey Absolute Decision Analysis model. Javed et al. (2020a, b, c) proposed EGM (1, 1, α, θ), a generalized and even form of the grey forecasting model. EGM (Even Form of Grey Model with first-order differential equation containing one variable) and DGM (Discrete Form of Grey Model with first-order differential equation containing one variable) are two of the four basic models of grey forecasting theory with EGM more suitable for making forecasts through non-exponential increasing data sequence (Liu et al. 2017). Recent studies (Arsy 2021; Laksito and Yudiarta 2021) have confirmed that the relative result of the proposed model is better than the original model.

3 Research methodology

Grey forecasting is an alternative process to forecasting. It includes witnessed overall energy and emissions forecasts (Zolfaghari and Golabi 2021, Qian and Sui 2021; Hamzacebi and Es 2014; Ma et al. 2019; Tsai 2016). Even grey forecasting model EGM (1, 1) and discrete grey forecasting model DGM (1, 1) are among the primary benchmarks of grey forecasting. The measures perform well in various conditions, yet the models may produce inaccurate forecasts when data contains more substantial uncertainty and a complicated problem. To overcome their deficiencies, EGM (1, 1, θ, α) and DGM (1, 1) were proposed by Javed and coworkers (Javed et al. 2020a, b, c). However, since the models are new, their validity on different problems must be verified.

The data used in this study includes daily closing prices of Multiple cryptocurrencies like Bitcoin (BTC), Bionic (BNC), Cardano (ADA), Dogecoin (DOGE), Ethereum (ETH), XRP (XRP) extracted from *Yahoo Finance (*2021), Fig. 1 shows the fluctuation in cryptocurrencies with the help of rolling window for 10, 20, 30, 40, and daily basis.

In the literature, various performance measures have been proposed in order to determine the accuracy of the forecasting approaches. In the current study, five performance measures such as normalized mean absolute percentage error (NMAPE), mean absolute percentage error (MAPE), mean square error (MSE), root mean square error (RMSE), and normalized root mean square error (NRMSE) has been used to measure the accuracy of GM (1, 1) and EGM (1, 1, α, θ). The following equations show the performance measures:

The Mean Square Error is

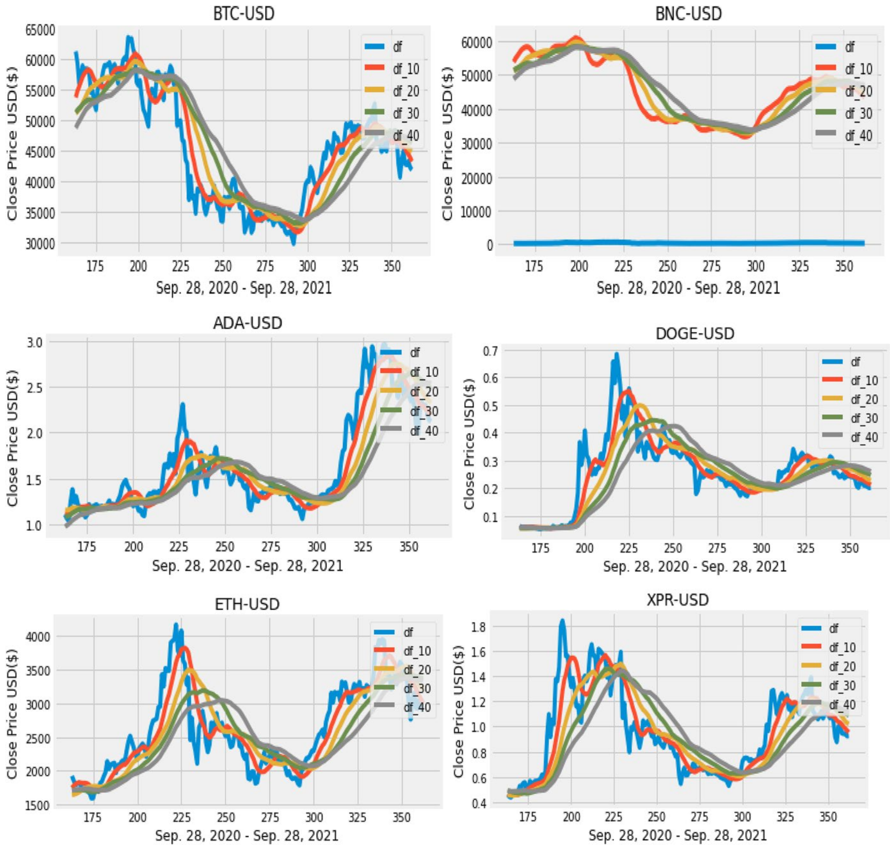

Fig. 1 Rolling window of BTC, BNC, ADA, DOGE, ETH, and XPR

$$\mathrm{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{At}\right|$$

$$\mathrm{NMAPE} = \frac{1}{n} \times \sum_{k=1}^{n}\left|\frac{y(t) - \hat{y}(t)}{\frac{1}{n}\sum_{k=1}^{n} y(t)}\right|$$

$$\mathrm{MSE} \ = \frac{\sum_{t=1}^{n}(At - Ft)^2}{N}$$

where A_t = Actual values at data time t, and F_t = forecast value at data time t

$$RMSE = \sqrt{\frac{1}{N}\sum_{i}^{N}(\mathrm{y(t)} - \hat{y}(\mathrm{t}))^2}$$

where N denotes the number of samples, $\hat{y}$ is the model predicted value, and y_i is the mean value of variable.

$$\text{NRMSE} = \frac{\sqrt{\sum_{i}^{N} (y(\mathrm{t}) - \hat{y}(\mathrm{t}))^2}}{\sqrt{\sum_{k=1}^{N} (\mathrm{y}(\mathrm{t}))^2}}$$

4 Results and discussion

Applying both GM (1, 1) and EGM (1, 1, α, θ) grey forecasting models, the most appropriate grey forecasting model was determined by using the data reserved (September 18, 2021–September 28, 2021) for the model building stage and then the validity of the selected model was tested with the test set of in-side of sample and out-side of the sample. The lowest value of accuracy measurement was found with EGM (1, 1, α, θ). The performance values of GM (1, 1) and EGM (1, 1, α, θ) for the in-sample testing (September 18, 2021–September 26, 2021) and out-Sample testing (September 27, 2021–September 28, 2021) is given in Table 3. The EGM (1, 1, α, θ) prediction model gives better results than the GM (1, 1) forecasting approach in the inside and outside samples. In order to make a fair comparison, the results obtained by EGM (1, 1, α, θ) were compared with the results of Javed et al. (2020a, b, c), Laksito and Yudiarta (2021) as well as the official results of Arsy (2021) and Wang et al. (2021). Comparative results of GM (1,1) and EGM (1, 1, α, θ) are given in Tables 1, 2 and Figs. 2, 3, 4, 5, 6, 7, and it is observed that the EGM (1, 1, α, θ) yields more accurate result. Finally, this study has predicted the closing price of cryptocurrencies from September 29, 2021, to October 07, 2021, by GM (1, 1) and EGM (1, 1, α, θ). Figures 2, 3, 4, 5, 6, 7 shows the forecasted values graphically, and Tables 1 and 2 depict the numerical forecasting values.

In this investigation, we studied the grey system techniques based upon sample characteristics of samples and measurements to predict five cryptocurrencies' prices. At the same time, most previous works leverage multiple prediction models, ARIMA, SutteARIMA, and machine learning algorithms in predicting stock price and cryptocurrencies. This study found another crucial novel approach grey system in EGM (1, 1, α, θ) and GM (1, 1) accurate prediction. We show that the sample's granularity and feature dimensions should be considered. The cryptocurrencies aggregated daily closing price, acquired from yahoo finance, and analysed using EGM (1, 1, α, θ) and GM (1, 1). Based on accuracy measure tools, prediction results using this model were very useful. Most of the results in the current study also outperform the benchmark results of other models like GM (1, 1) algorithms. The findings of this study can be used for the prediction process in any other field.

4.1 Discussion

The results shown in the above tables clearly display the accurate measurement of the proposed prediction model EGM (1, 1, α, θ) and GM (1, 1) grey system approach. Errors in the forecasting approach EGM (1, 1, α, θ) are less than in GM (1, 1). The result also proves that the experiments carried out align with the actual value of different cryptocurrencies. Studies have stated that various types of uncertainties influence the price of cryptocurrencies. The ambiguity associated with Cryptocurrencies' price is one of the reasons that create fluctuations in the markets (Lucey et al. 2021), (Antonakakis et al. 2019), (Foglia and Dai 2021). A research work found a strong momentum effect in BTC and ETH market and

Table 1 Closing price of BTC, BNB, and ADA in US-Doller (USD)

	BTC			BNB			ADA		
Year	Actual	GM (1, 1)	EGM (1, 1, α, θ)	Actual	GM (1, 1)	EGM (1, 1, α, θ)	Actual	GM (1, 1)	EGM (1, 1, α, θ)
18/09/21	48,278.363	48,278.363	48,278.363	410.809	410.809	410.809	2.370	2.370	2.370
19/09/21	47,260.219	44,406.649	44,295.425	408.472	386.065	384.016	2.282	2.148	2.168
20/09/21	42,843.801	44,145.644	44,029.486	361.966	380.137	378.097	2.064	2.167	2.192
21/09/21	40,693.676	43,886.173	43,765.143	344.535	374.301	372.268	1.987	2.186	2.215
22/09/21	43,574.508	43,628.227	43,502.388	379.440	368.553	366.529	2.266	2.205	2.237
23/09/21	44,895.098	43,371.797	43,241.210	383.820	362.894	360.879	2.331	2.224	2.259
24/09/21	42,839.750	43,116.874	42,981.600	355.316	357.322	355.316	2.281	2.244	2.280
25/09/21	42,716.594	42,863.450	42,723.548	349.880	351.836	349.839	2.302	2.263	2.302
26/09/21	43,208.539	42,611.515	42,467.046	344.182	346.434	344.446	2.208	2.283	2.323
27/09/21	42,235.730	42,361.061	42,212.084	336.191	341.114	339.137	2.136	2.303	2.344
28/09/21	41,861.668	42,112.079	41,958.653	335.951	335.877	333.909	2.122	2.323	2.366
29/09/21		41,864.560	41,706.743		330.719	328.761		2.344	2.388
30/09/21		41,618.496	41,456.345		325.641	323.693		2.364	2.409
01/10/21		41,373.879	41,207.451		320.641	318.704		2.385	2.431
02/10/21		41,130.699	40,960.052		315.718	313.791		2.405	2.453
03/10/21		40,888.948	40,714.137		310.870	308.954		2.426	2.475
04/10/21		40,648.619	40,469.699		306.097	304.191		2.448	2.497
05/10/21		40,409.702	40,226.729		301.397	299.502		2.469	2.520
06/10/21		40,172.189	39,985.217		296.769	294.885		2.491	2.542
07/10/21		39,936.073	39,745.155		292.212	290.339		2.512	2.565
a		0.0059	0.0060		0.0155	0.0155		-0.0087	-0.0086
b		44,822.2644	44,719.6548		395.4167	393.3888		2.1184	2.1297
α			1			1			0.99408496
θ			0			0.122671869			0

Table 2 Closing price of DOGE, ETH, and XPR in US-Doller (USD)

Year	DOGE			ETH			XPR		
18/09/21	Actual	GM (1, 1)	EGM (1,1,α,θ)	Actual	GM (1, 1)	EGM (1, 1, α, θ)	Actual	GM (1, 1)	EGM (1, 1, α, θ)
19/09/21	0.241	0.241	0.241	3432.018	3432.018	3432.018	1.076	1.076	1.076
20/09/21	0.233	0.221	0.220	3329.448	3087.959	3081.283	1.048	0.977	0.975
21/09/21	0.207	0.219	0.218	2958.993	3069.963	3062.606	0.917	0.972	0.970
22/09/21	0.201	0.217	0.216	2764.431	3052.072	3044.043	0.876	0.967	0.965
23/09/21	0.225	0.215	0.214	3077.868	3034.286	3025.592	1.004	0.962	0.960
24/09/21	0.225	0.213	0.212	3155.524	3016.602	3007.253	1.002	0.958	0.955
25/09/21	0.209	0.211	0.210	2931.669	2999.022	2989.025	0.946	0.953	0.950
26/09/21	0.209	0.209	0.208	2925.566	2981.545	2970.908	0.941	0.948	0.945
27/09/21	0.205	0.207	0.206	3062.265	2964.169	2952.900	0.945	0.943	0.940
28/09/21	0.200	0.206	0.205	2934.139	2946.894	2935.002	0.924	0.939	0.935
29/09/21	0.200	0.204	0.203	2900.799	2929.720	2917.212	0.925	0.934	0.930
30/09/21		0.202	0.201		2912.647	2899.530		0.929	0.925
01/10/21		0.200	0.199		2895.672	2881.955		0.925	0.921
02/10/21		0.198	0.197		2878.797	2864.487		0.920	0.916
03/10/21		0.196	0.195		2862.020	2847.124		0.916	0.911
04/10/21		0.195	0.193		2845.341	2829.867		0.911	0.906
05/10/21		0.193	0.192		2828.759	2812.714		0.907	0.902
06/10/21		0.191	0.190		2812.273	2795.665		0.902	0.897
07/10/21		0.189	0.188		2795.884	2778.720		0.898	0.892
a		0.188	0.186		2779.590	2761.877		0.893	0.888
b		0.0091	0.0093		0.0058	0.0061		0.0050	0.0052
α		0.2244	0.2235		3117.0521	3111.5250		0.9846	0.9833
θ			1			1			1

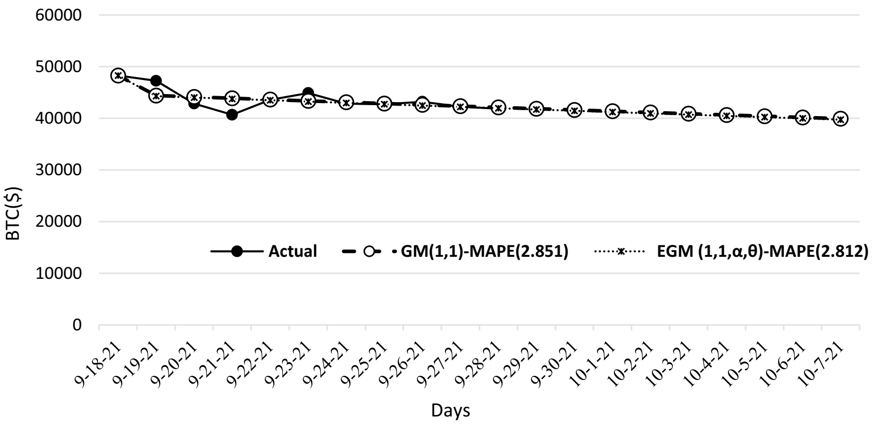

Fig. 2 Actual and predicted values of BTC ($)

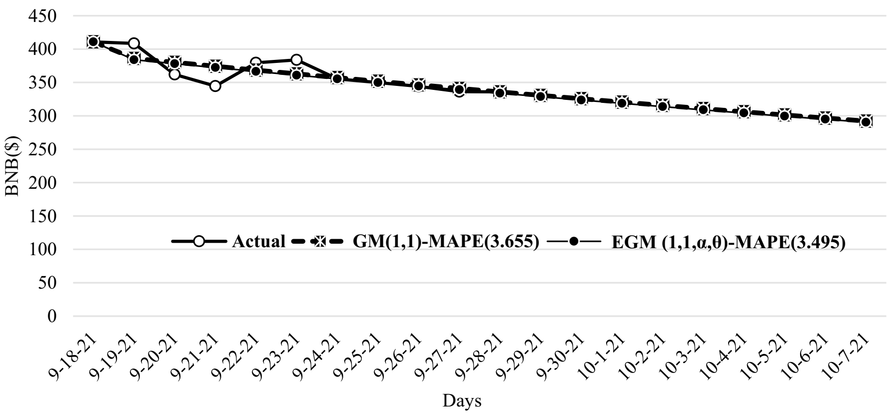

Fig. 3 Actual and predicted values of BNC ($)

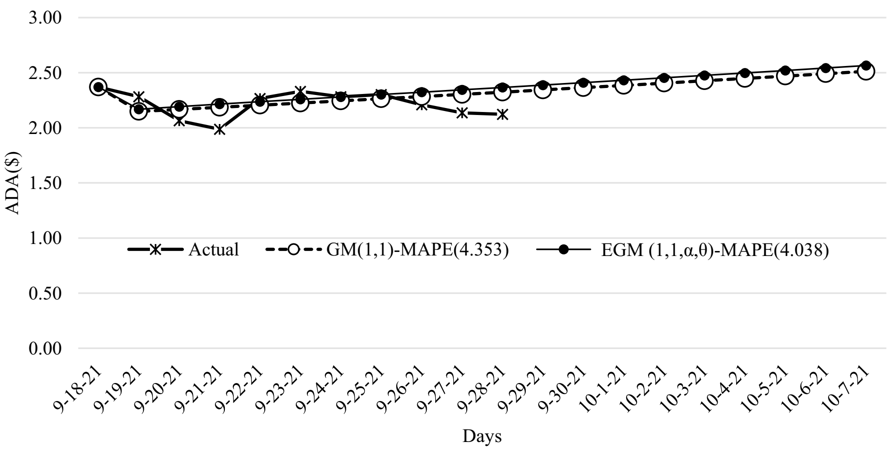

Fig. 4 Actual and predicted values of ADA ($)

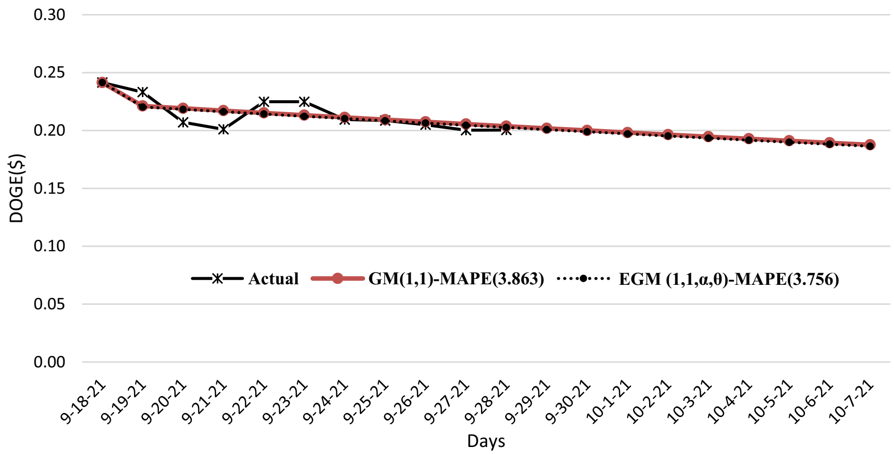

Fig. 5 Actual and predicted values of DOGE ($)

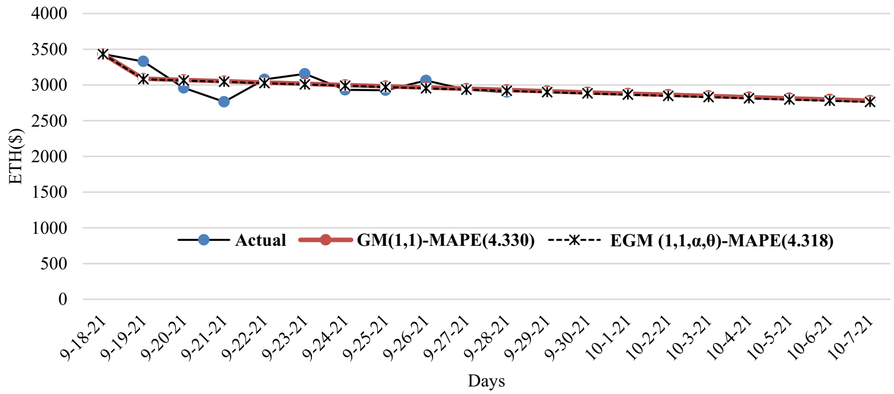

Fig. 6 Actual and predicted values of ETH ($)

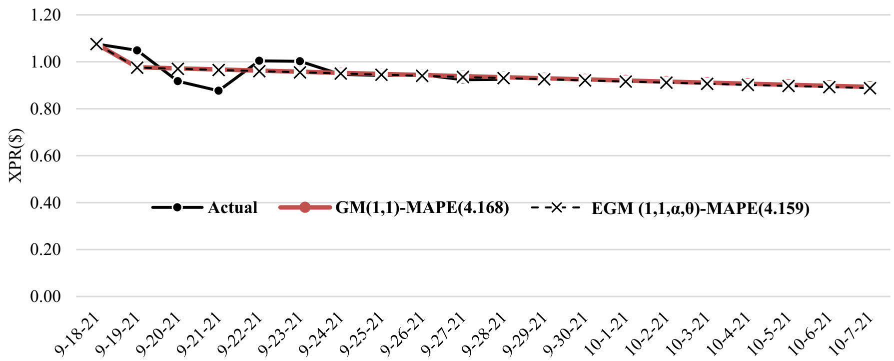

Fig. 7 Actual and predicted values of XPR ($)

Table 3 Evaluation of Accuracy measurement of all Cryptocurrencies

BTC	In-sample testing (September 18, 2021, to September 26, 2021)					Out-Sample testing (September 27, 2021, to September 28, 2021)				
	NMAPE	MAPE	MSE	RMSE	NRMSE	NMAPE	MAPE	MSE	RMSE	NRMSE
EGM (1, 1)	0.000	2.851	2,867,536.388	1693.380	0.039	0.000	0.4475	4982.5946	70.5875	0.0047
EGM (1, 1, α, θ)	0.000	2.813	2,850,978.243	1688.484	0.039	0.000	0.1438	39,206.5888	198.0065	0.0017
BNB										
EGM (1, 1)	0.010	3.656	290.058	17.031	0.046	0.002	0.7432	6.4220	2.5342	0.0104
EGM (1, 1, α, θ)	0.010	3.495	285.951	16.910	0.047	0.002	0.7419	12.1207	3.4815	0.0075
ADA										
EGM (1, 1)	1.965	4.353	0.013	0.112	0.048	3.903	8.6452	0.0514	0.2268	0.0868
EGM (1, 1, α, θ)	1.823	4.039	0.011	0.107	0.051	4.794	10.6206	0.0341	0.1848	0.1065
DOGE										
EGM (1, 1)	18.034	3.864	0.000	0.010	0.046	10.038	2.1506	0.0000	0.0034	0.0221
EGM (1, 1, α, θ)	17.532	3.756	0.000	0.010	0.047	7.518	1.6107	0.0000	0.0044	0.0169
ETH										
EGM (1, 1)	0.001	4.330	24,065.948	155.132	0.051	0.000	0.7159	135.0604	11.6216	0.0077
EGM (1, 1, α, θ)	0.001	4.318	23,982.515	154.863	0.051	0.000	0.2976	499.5643	22.3509	0.0040
XPR										
EGM (1, 1)	4.343	4.169	0.003	0.050	0.052	1.344	1.2902	0.0001	0.0089	0.0133
EGM (1, 1, α, θ)	4.333	4.160	0.003	0.050	0.052	0.942	0.9042	0.0002	0.0123	0.0097

a reversion effect in XRP and EOS when large fluctuation occurs in cryptocurrencies price (Cheng et al. 2019). On the other hand, Grey System Theory and its models have been best known for their reliable predictions through the data containing uncertainty or data associated with an uncertain system (Javed et al. 2020a, b, c; Arsy 2021; Feng et al. 2012 and Hamzacebi and Es 2014). The grey forecasting model EGM (1, 1, α, θ) has been used to evaluate the Six leading Cryptocurrencies based on their actual and predicted values. BTC is projected to be 39,745.155 (USD), BNB 290.339 (USD), and ADG 2.565 (USD) by October 07, 2021; thus, policymakers should focus on the predicted values of EGM (1, 1, α, θ) that is likely to fluctuate, as shown in Figs. 2, 3, 4. Generally, the trend of BTC is stable in the short run; however, BNB is falling slowly. It is important to note that the volume of ADA is relatively low, but the status of this cryptocurrency is moving in an upward direction. In admission, the trend of these cryptocurrencies is relatively more predictable in the short run. The cryptocurrency ETH is projected to be 2778:720 while predicted value DOGE and XPR 0.188 and 0.892 respectively by October 07, 2021, as shown in Table 2 and Figs. 5, 6, 7. Generally, the trend is decreasing; however, the BTC cryptocurrency is likely to maintain its status. BNC continues to improve status by a slight moment in an upward direction, as shown in Fig. 3. In Tble 3, we compare the NMAPE, MAPE, MSE, RMSE, and NRMSE for the two above discussed prediction approaches, and we see both forecasting models are performed well to predict time series. The table is given as follows:

The accuracy level of the grey system theory models: GM (1, 1) and EGM (1, 1, α, θ) can be compared with the help of Table 3. On account of the final prediction accuracy level of NMAPE, MAPE in Table 3, the proposed model of the grey system theory EGM (1, 1, α, θ) is better than model GM (1, 1). However, the mean absolute percentage error (MSE) is relatively low with GM (1, 1), but MAPE is more accurate in error percentage calculation. In addition, ample of the study found more accuracy with the Grey System prediction rather than another approach of prediction: such as Lotfalipour et al. (2013) found more accurate results of CO_2 emission with the application of grey system approach in Iran; A study conducted by Wang et al. (2018) shows that the combination of MNGM-ARIMA approach has the lowest mean absolute percentage error (MAPE).

4.2 Conclusion and suggestions

In this study, the forecasting performance of the Grey System Theory GM (1, 1) has been improved by applying a new algorithm which is called Conformable fractional accumulated databased EGM (1, 1) with the weighted background value or EGM (1, 1, α, θ). The horizontal adjustment coefficient (q) and the length of subsequences (k), which are important factors in order to develop a successful model, have been determined (Javed et al. 2020a, b, c). Then, two forecasting approaches called iterative and direct forecasting were applied. The results show the superiority of the direct forecasting approach over the iterative one. This superiority results from the usage of real past data in long-term forecasting, while the iterative forecasting approach uses the predicted values. EGM (1, 1, α, θ) forecasted values of Cryptocurrencies for September 28, 2021, to October 07, 2021, as explained in Tables 1, 2. The projected value of different cryptocurrencies: BTC (39,745.155), BNC (290.339), ADA (2.565), DOGE (0.188), ETH (2778.720), and XPR (0.892) by October 07, 2021. Since forecast values are of great importance in guiding future investments, decision-makers must consider various forecasting methods and select the best forecast performance. This study suggests that the performance of the existing prediction methods, such as EGM (1, 1, α, θ), can still be improved in light of the trends of cryptocurrencies. These results may guide policymakers and investors in a situation to know the appropriate decision of forecasting in various cryptocurrencies. In order to ensure the security of investors, it needs to determine an appropriate policy by the government to make a decision about investment in cryptocurrencies, take measures and make investments.

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Data availability The data that support the findings of this study are openly available on request.

Declarations

Conflict of interest The authors declare no competing interests.

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