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AN EMPIRICAL ANALYSIS OF CRYPTOCURRENCY TRENDS FOR FINANCIAL DECISIONS

Jun Yup Kim, Moonseong Kang, Lynn J. Park, Yungha Kim
New York University, Wilbraham and Monson Academy, Taejeon Christian International School, Seoul Scholars International

ABSTRACT. Cryptocurrencies have recently gained closer attention based on its benefits such as cross-border fund transfer and decentralized financial control. Additional financial benefits are expected through better analysis of market and other factors affecting cryptocurrencies. Blockchain analysis is one way to obtain a better understanding of cryptocurrencies. This study explores cryptocurrencies from various aspects, including recent trends in famous cryptocurrencies, and analyzes their correlations based on top 10 cryptocurrencies including Bitcoin, Ethereum, Ripple, Bitcoin Cash, EOS, Stellar, Litecoin, Cardano, Tether, and TRON. An analytic tool called Tableau is used to visually depict analysis results for deeper insights in cryptocurrencies. Future cryptocurrency prices are forecasted using the exponential smoothing method based on historical values. The study also calculates different types of errors in the computation of predicted values of cryptocurrencies using Tether and Stellar.

KEYWORDS: Cryptocurrency, Token, Bitcoin, Financial Decision, CoinMarketCap, Empirical Analysis, Market Capacity, Decentralized System.

1. Introduction

A cryptocurrency is a peer-to-peer digital exchange system using cryptography to generate and distribute the currency unit. This process requires the distributed verification of transactions without any central authority, and transaction verification confirms no duplicate transactions. Cryptocurrencies use various mining technologies for specific requirements. For instance, cryptocurrencies restrict the number of transactions validated per unit time and focus on achieving fast and lightweight services. Some mining algorithms are deliberately memory-intensive, whereas others are computationally costly [1].

A cryptocurrency is a system of token exchanges between users that is verifiable through the application of the same cryptography principles and encryption as the Internet. Cryptocurrencies are typically implemented as distributed peer-to-peer systems based on blockchain technology, which is seen to have the potential to revolutionize payment and financial systems. There are many data mining techniques and proposals for improving the privacy of cryptocurrencies [2].

Several data mining techniques have been proposed to improve the privacy of cryptocurrencies. Such methods range from Bitcoin-compatible methods of “mixing” (or “joining”) coins with each other with the help data mining techniques to entirely new cryptocurrency privacy protocols. Perhaps the most radical proposal is Zero Cash, an alternative cryptocurrency design. Zero Cash uses cutting-edge cryptography to hide information from the blockchain except for the existence of transactions, and each transaction requires a publicly verifiable proof. The proof ensures that the spent amount is no more than the available amount for the sender and the receiver [3].

A key security risk in cryptocurrencies is the security endpoint with respect to data mining techniques or the device storing private keys for controlling one’s coins. The cryptocurrency ecosystem has been plagued by fraud and losses from lost devices, broken hard drives, malware, and hacking. Unlike fiat currencies, cryptocurrency theft is instantaneous, irreversible, and generally anonymous. In this regard, one key area cryptocurrencies is the so-called smart contract, an agreement between two or more parties that can be automatically enforced without requiring some intermediary [4].

Fair exchange between two parties typically involves two players for exchanging items. Each party holds an item to be transferred and some expectation of the other party's item to be received for their transaction. Fair exchange is executed without parties necessarily trusting each other. Such cases include commercial scenarios such as payment for receipt, online purchase, digital contract signing, and certified mail [5]. Several factors can affect fair exchange between two parties in the field of cryptocurrencies:

i. Effectiveness: If both parties behave correctly and are willing to exchange their transaction information, then the protocol succeeds.
ii. Fairness: There are two possible notions of fairness. In strong fairness, at protocol termination, both parties get what they want (the exchange succeeds) or neither does (the exchange fails). For weak fairness, an honest party can prove to an (external) arbiter that the other party receives (or can still receive) the item expected by the latter.
iii. Timeliness: Regardless of the behavior of the other party, an honest party can be certain that the exchange will be completed (either succeed or fail) at a certain point in time. At the completion of the protocol, the state of exchange is final from that party's perspective (fairness achieved by the protocol will not change from strong to weak).
iv. Noninvasiveness: The protocol should allow the exchange of arbitrary items without any demands on their structures. For example, a protocol is invasive if it requires anyone who wants to verify the exchanged signature to access and perform some check on the blockchain.

Many software tools have been developed to analyze trends in cryptocurrencies. Such tools are designed to retrieve, analyze, transform, and report data for decision-making processes and generally read data that are previously stored in a data warehouse. Such tools are currently being used for strategic corporate goals such as KPI measurement, cost-effective deployment of resources, and business health planning. These solutions can help facilitate better decision-making processes at higher levels of management authority. The present study makes use of a tool known as Tableau to study trends in the cryptocurrency market cap [6] and exponential smoothing for forecasting of cryptocurrency values [7].

The rest of this paper is organized as follows: Section 2 explores related research. Section 3 details the proposed work. Section 4 describes the experimental setup, including the dataset on cryptocurrencies, performance metrics, and exponential smoothing. Section 5 presents the experimental results using top 10 datasets for cryptocurrencies. Section 6 concludes and provides a direction for future research.

2. Literature Survey

Many researchers have analyzed cryptocurrency trends using various techniques. Mukhopadhyay and Skjellum [1] emphasizes that cryptocurrencies have emerged as an important financial software system for exchange between two different clients in different network segments and stated that cryptocurrencies rely on a secure distributed ledger data structure with mining being an integral part of such systems. Mining adds records of past transactions to the distributed ledger known as Blockchain. This allows users to reach a secure and robust consensus for each transaction and introduces wealth in the form of new units of currency.

Cryptocurrencies lack a central authority to mediate transactions because they are designed as a peer-to-peer system. Therefore, researchers rely on miners to validate transactions, and cryptocurrencies require powerful and secure mining algorithms.

Tschorsch and Scheuermann [2] state that, besides attracting a billion-dollar economy to increase the level of the market value of the currency, Bitcoin has revolutionized the field of digital currencies, inducing close scientific attention along the way. They unroll and structure manifold results and research directions and introduce the Bitcoin protocol and its building blocks. In the process, they deduce fundamental structures and present insights into the Bitcoin protocol and its applications.

Liu [3] focuses on the success of Bitcoin and finds more than 500 cryptocurrencies, with most being simple variants of Bitcoin. One main reason behind the growing adoption of blockchain-based cryptocurrencies is their promise of low-cost global payments without the need for bank accounts or difficult registration processes.

Narayanan and Miller [4] state that cryptocurrency research has a decades-long record but that decentralized cryptocurrencies (starting with Bitcoin in 2009) have really started the trend. Aside from being a payment mechanism "native to the Internet," the blockchain seen as a way to store and transact everything from property records to certificates for anything of financial value.

Sin and Wang [5] explore the relationship between Bitcoin features and the next-day change in the price of Bitcoin using an artificial neural network approach called the genetic algorithm-based selective neural network ensemble, which is constructed using the multi-layered perceptron as the base model for each neural network in the ensemble. For a better understanding, the ensemble is used to predict the next-day direction of the price of Bitcoin for a given set of approximately 200 features of the cryptocurrency over a 2-year period. Over a span of 50 days, a trading strategy based on the ensemble is compared to the "previous day trend following" trading strategy through back-testing for cryptocurrency use.

Phillips and Gorse [8] focus on financial price bubbles previously linked to the epidemic-like spread of an investment idea. Such bubbles are often observed in cryptocurrency prices for exchanges between one network segment and another. They predict such bubbles for a number of cryptocurrencies using a hidden Markov model previously used for detecting influenza epidemic outbreaks. Their proposal is based on the behavior of novel online social media indicators. To validate the methodology, they construct a trading strategy and test it using historical data to generate inferences about an organization's decision-making process.

Vujicic et al. [9] approach blockchain technology as a relatively new IT approach. As one of its first implementation, Bitcoin has gained much attention. Bitcoin and Ethereum today are well-known cryptocurrencies as a result of their market presence, and they are based on blockchain technology, which is intended to promote a trust mechanism in a peer-to-peer network based on the consensus of a majority of nodes.

Denget et al. [10] found computers to beat experienced traders in financial asset trading. They address this challenge by introducing a recurrent deep neural network (NN) for real-time financial signal representation and trading. The proposed model is inspired by two biological learning concepts of deep learning (DL) and reinforcement learning (RL). In their framework, the DL element automatically senses the dynamic market condition for feature learning, and then the RL module interacts with deep representation to make trading decisions for ultimate rewards.

Chan and Osterrieder [11] analyze statistical properties of Bitcoin, the most prominent example in the current scenario of market segments. They characterize the exchange rate versus the U.S. dollar by fitting parametric distributions and show clearly abnormal returns. However, no single distribution fits well jointly to all cryptocurrencies considered, and the researchers found that for the most popular cryptocurrencies such as Bitcoin and Litcoin, the generalized hyperbolic distribution provides the best fit, whereas for smaller cryptocurrencies, the normal inverse Gaussian distribution, generalized t distribution, and Laplace distribution give a good fit.

Radityo et al. [12] highlight that cryptocurrency trade is now a popular investment. The cryptocurrency market is treated similarly to foreign exchange and stock markets. However, because of its volatility, there is a need for a prediction tool for investors in cryptocurrency trade. Today, artificial neural network (ANN) tools are widely used in stock and foreign exchange market predictions. The researchers generate predictions based on data mining algorithms.

Laskowski and Kim [13] emphasize that the blockchain represents a technology for establishing a shared and immutable version of truth among a network of participants who do not trust one another and thus has the potential to disrupt any financial or other industries relying on third parties for that trust. For a deeper understanding of the current blockchain ecosystem, a scalable proof-of-concept pipeline for analyzing multiple streams of semi-structured data from social media is demonstrated based on open source components. They also suggest the Deep Web as well as conventional social media.

These findings reveal that cryptocurrencies are gaining greater interest due to its benefits such as cross-border fund transfers and decentralized control. Many financial benefits can be gained through a better understanding of the market and other factors affecting cryptocurrencies. Blockchain analysis is one way for this understanding. The accurate forecasting of cryptocurrency values based on historical values can lead to financial gains, and there is thus a need for analyzing various factors influencing cryptocurrencies for a better prediction method for future values of cryptocurrency.

3. The Proposed Work

This study analyzes various parameters related to cryptocurrencies, including Market Open, High, Low, Close, Volume, and Market Cap, and presents deeper insights by analyzing different parameters and their relationships using the correlation coefficient as the metric. The study also presents a deep pattern analysis of the market cap for top 10 cryptocurrencies using Tableau. Finally, the proposed work involves the prediction of future values of cryptocurrencies using the exponential smoothing method, and predicted values show themselves to be useful for making investment decisions.

4. Experimental Setup

This study conducts a set of experiments to analyze cryptocurrency trends. This section details the dataset used in this study and various performance metrics for measuring the relationships between different parameters influencing cryptocurrencies. The section also describes the basics of the exponential smoothing method, which is used to forecast future cryptocurrency values.

4.1 Cryptocurrency Datasets

This study utilizes a publicly available online dataset from Coin Market Cap [14]. The downloaded dataset provides historical data on cryptocurrencies with the timestamps in addition to basic fields including Date, New, Open, High, Low, Close, Volume, and Market Cap. The dataset can be downloaded using website-scraping techniques. The dataset requires minor preprocessing before the experiment. The dataset analysis includes 10 cryptocurrencies with the highest market cap as of August 10, 2018.

4.2 Performance Metrices:

The performance of the system and the relationship between variables can be measured in several ways. This study uses the following metrics:

i. Correlation Coefficient

The correlation coefficient gives the relationship between two variables and their types such as exponential, polynomial, and algorithmic . The most widely used performance metric is the Person correlation coefficient r:

$$r = \frac{n(\sum zy)-(\sum z)(\sum y)}{\sqrt{[n\sum z^2-(\sum z)^2]\,[n\sum y^2-(\sum y)^2]}}\,. \qquad (1)$$

The correlation coefficient is used to measure the strength of the relationship between two variables [15], and the correlation coefficient value can be interpreted as follows:

- A correlation coefficient of 1 means that for every positive increase in a variable, there is a positive increase of a fixed amount in the other.
- A correlation coefficient of -1 means that for every positive increase in one variable, there is a negative decrease of a fixed amount in the other.
- A correlation coefficient of 0 means that for every increase, there is no positive or negative increase. The two variables are not related.

Researchers divide the category and strength of the relationship between variables as follows: A value 0.2 indicate a minimal relationship, a value between 0.4 and .6 indicates a moderate relationship, and a value of 0.8 indicates a strong relationship. This process can be applied to any kind of real-life variables.

ii. Mean Absolute Scaled Error (MASE)

The MASE metric calculates the accuracy of forecasted values to expected values [7]:

$$\text{MASE} = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{|f_t|}{\frac{1}{T-1}\sum_{t=2}^{T}|Z_t - Z_{t-1}|}\right) = \frac{\sum_{t=1}^{T}|f_t|}{\frac{T}{T-1}\sum_{t=2}^{T}|Z_t - Z_{t-1}|}. \qquad (2)$$

For a given period, the forecast error is calculated by subtracting the forecast value (P_t) from the actual value (Z_t) as $f_t = Z_t - P_t$.

iii. Systematic Mean Absolute Percentage Error (SMAPE)

This metric provides accuracy in terms of the percentage error. Here P_t represents the forecasted value, and K_t represents the actual value [16]. For the total count ***n***, the formula for calculating SMAPE is as follows:

$$\text{SMAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\frac{|P_t - K_t|}{(|K_t| + |P_t|)/2}\,. \qquad (3)$$

iv. Mean Absolute Error (MAE)

MAE measures the difference between two continuous variables. Suppose a scattered plot is created by *n* points and any random point *i* with coordinates (yy_i, xx_i). Then MAE calculates the average vertical distance corresponding to each point and the y = x line [17]. The formula for calculating MAE is as follows:

$$\text{MAE} = \frac{\sum_{i=1}^{n}|yy_i - xx_i|}{n} = \frac{\sum_{i=1}^{n}|e_i|}{n}\,. \qquad (4)$$

v. Root Mean Square Error (RMSE)

RMSE measures the standard deviation of predicted errors and indicates the trend in how intensively data are spread around the line of the best fit [18]:

$$\text{RMSE} = \sqrt{\overline{(P - A)^2}}, \qquad (5)$$

where *P* is the predicted value, *A* is the actual value, and the bar represents the mean. This formula can be extended to be rewritten as follows:

$$\text{RMS}_{\,0} = \left[\sum_{i=1}^{M}\left(y_{f_i} - y_{0i}\right)^2 / M\right]^{1/2}, \qquad (6)$$

where

- Σ = summation (“add up”),
- $\left(y_{f_i} - y_{0i}\right)^2$ = differences squared, and
- M= Sample size.

4.3 Exponential Smoothing Method

This study employs the exponential smoothing method to forecast future cryptocurrency values based on historical data [19]. To forecast future values, exponential smoothing weights of past observations with exponential declining weights are computed. The general expression for exponential smoothing at time t is given as follows:

$$Pt=\alpha yt-1+(1-\alpha)\, P_{t-1}\; 0<\alpha\leq 1 t\geq 3, \qquad (7)$$

where α is the smoothing constant whose value is adjusted to give most precise forecasted values.

5. Experimental Results and Discussion

This section presents the experimental results for various cryptocurrencies. The correlation coefficient and the squared correlation coefficient are calculated between various metrics. These metrics are further used for the relationships between dominating factors in cryptocurrencies, their trends, and Market Cap values.

5.1 Bitcoin Results

Bitcoin is the first peer-to-peer decentralized payment network powered only by users. Its network entails the sharing of a public ledger called the blockchain, in which each transaction has a digital signature. It includes the process of mining where the computing power of the system is used to secure and process transactions and keep all users in a synchronized manner. The average time to find a block must be less than 10 minutes during the mining process. The values of the correlation coefficient between various parameters related to Bitcoin, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 1, Fig. 1, and Eq. 8, respectively.

Table 1. Value of correlation coefficient between various metrics for Bitcoin

	*Open**	*High*	*Low*	*Close***	*Volume*	*Market Cap*
Open*	1					
High	0.998860073	1				
Low	0.997974573	0.997974	1			
Close**	0.997417751	0.999115	0.998669	1		
Volume	0.946539404	0.949922	0.936034	0.944573	1	
Market Cap	0.999866658	0.99858	0.998036	0.997262	0.945863	1

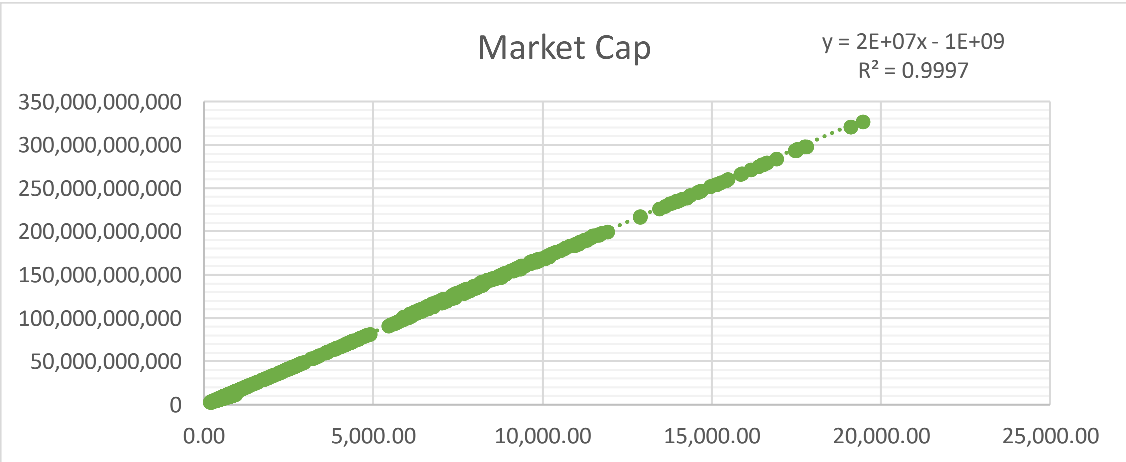

Fig. 1. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for Bitcoin

$$\text{Market\_Cap} = (2E+07) * \text{Market\_Open} - 1E+09. \quad (8)$$

5.2 Ethereum Results

Ethereum provides a decentralized platform that makes use of smart contracts. That is, it is based on programming that makes use of the blockchain with shared global infrastructure. With the blockchain, any user can set a node that can replicate important data for all remaining nodes per the agreement. The values of the correlation coefficient between various parameters related to Ethereum, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 3, Fig. 2, and Eq. 9, respectively.

Table 3. Value of correlation coefficient between various metrics of Ethereum

	*Open**	*High*	*Low*	*Close***	*Volume*	*Market Cap*
Open*	1					
High	0.998702	1				
Low	0.996765	0.99683	1			
Close**	0.996809	0.998631	0.99814	1		
Volume	0.904012	0.914192	0.888097	0.905001	1	
Market Cap	0.999758	0.9982	0.996741	0.996462	0.903138	1

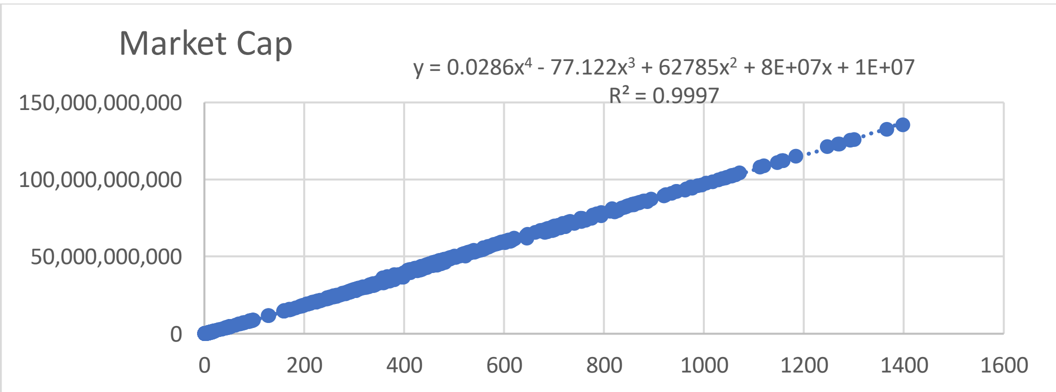

Fig. 2. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for Ethereum

$$\text{Market\_Cap} = 0.0286*\text{Market\_Open}^4 - 77.122*\text{Market\_Open}^3 + 62785*\text{Market\_Open}^2 + (8E+07) * \text{Market\_Open} + 1E+07. \quad (9)$$

5.3 Ripple Results

Ripple makes uses of RippleNet for connecting banks, payment providers, and exchanges. Cross-border payments can be made on a real-time basis along with real-time tracking, and its network increases remittance revenue. The values of the correlation coefficient between various parameters related to Ripple, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 5, Fig. 3, and Eq. 10, respectively.

Table 5. Value of correlation coefficient between various metrics of Ripple

	*Open**	*High*	*Low*	*Close***	*Volume*	*Market Cap*
Open*	1					
High	0.994761	1				
Low	0.992967	0.991365	1			
Close**	0.991656	0.996399	0.995322	1		
Volume	0.766375	0.810141	0.748187	0.790684	1	
Market Cap	0.999935	0.994504	0.993122	0.991607	0.76476	1

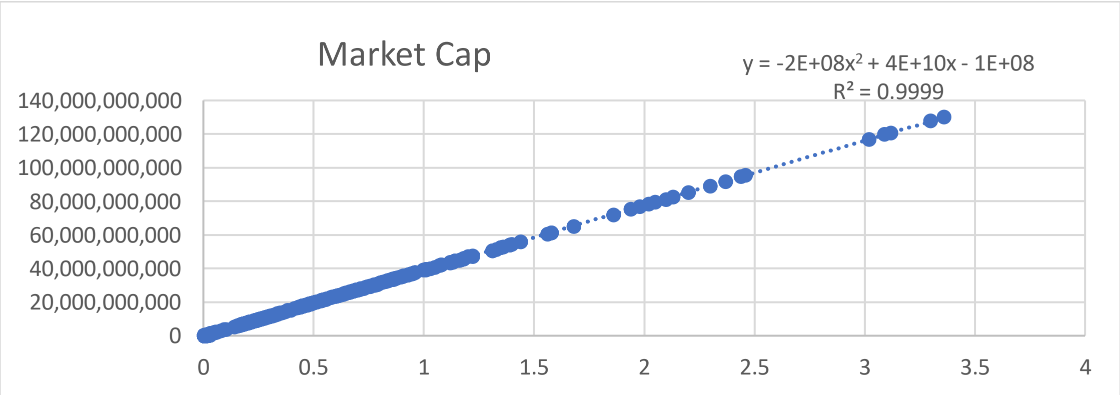

Fig. 3. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for Ripple

$$Market\_Cap = (-2E+08) * Market\_Open^2 + 4E+10 * Market\_Open - 1E+08. \quad (10)$$

5.4 Bitcoin Cash Results

Bitcoin Cash is an electronic cash system based on a peer-to-peer network. Bitcoin Cash came into existence when the Bitcoin community and the Bitcoin project divided. Bitcoin Cash has a fixed supply, and the protocol used by Bitcoin Cash ensures a total of 21 million coins. The values of the correlation coefficient between various parameters related to Bitcoin Cash, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 7, Fig. 4, and Eq. 11, respectively.

Table 7. Value of correlation coefficient between various metrics of Bitcoin Cash

	*Open**	*High*	*Low*	*Close***	*Volume*	*Market Cap*
Open*	1					
High	0.982391	1				
Low	0.984815	0.978442	1			
Close**	0.97707	0.991178	0.988243	1		
Volume	0.504445	0.618296	0.496618	0.576114	1	
Market Cap	0.999878	0.981614	0.985147	0.976824	0.501007	1

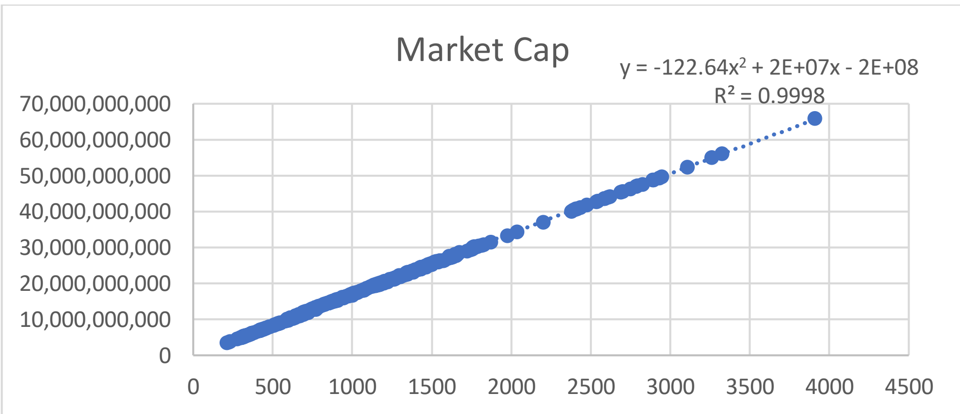

Fig. 4. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for Bitcoin Cash

$$\text{Market\_Cap} = -122.64*\text{Market\_Open}^2 + 2E{+}07*\text{Market\_Open}^2 - 2E{+}08. \quad (11)$$

5.5 EOS Results

EOS makes use of the open source MIT license EOSIO software with which the blockchain architecture is implemented and vertical and horizontal scaling of decentralized applications can be done. It can handle millions of transactions per second, and application scheduling, authentication, database synchronization, and asynchronous communication are some of its key features. With the EOSIO private key, the EOS blockchain can be accessed. The repository can be forked and interested users can start their own blockchains. The values of the correlation coefficient between various parameters related to EOS, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 9, Fig. 5, and Eq. 12, respectively.

Table 9. Value of correlation coefficient between various metrics of EOS

	*Open**	*High*	*Low*	*Close***	*Volume*	*Market Cap*
Open*	1					
High	0.992909	1				
Low	0.992295	0.990718	1			
Close**	0.987299	0.995789	0.993682	1		
Volume	0.806118	0.838183	0.79274	0.826183	1	
Market Cap	0.970624	0.957762	0.971448	0.958491	0.80712	1

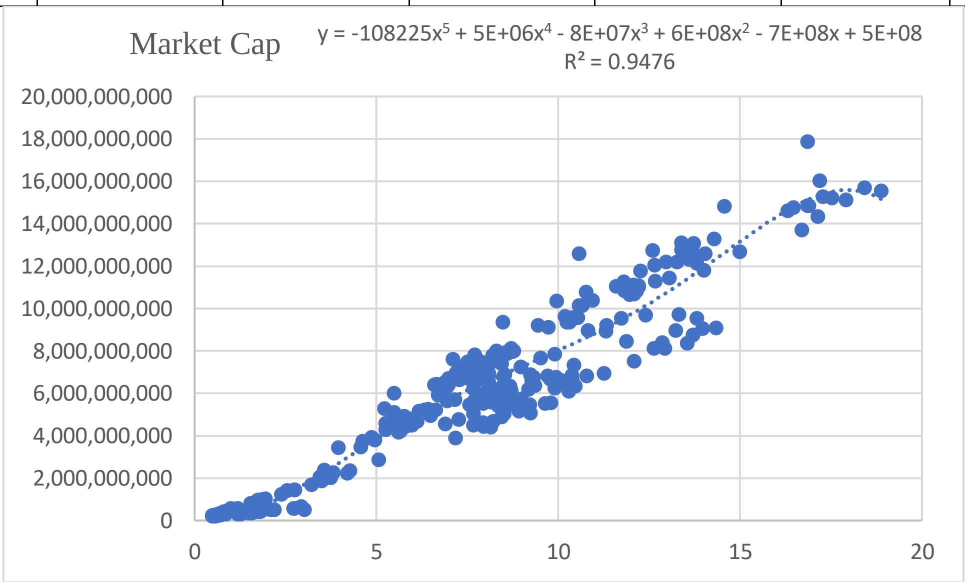

Fig. 5. Trendline and CCQ between Market Cap (y-axis) and Market Low (x-axis) for EOS

$$\text{Market Cap} = -108225*\text{Market\_Low}^5 + 5E{+}06*\text{Market\_Low}^4 - 8E{+}07*\text{Market\_Low}^3 + 6E{+}08*\text{Market\_Low}^2 - 7E{+}08*\text{Market\_Low} + 5E{+}08. \quad (12)$$

5.6 Stellar Results

Stellar makes use of decentralized servers with a distributed ledger. All servers continuously communicate with one another and thus synchronize the ledger in every 2 to 5 seconds. This mechanism is known as a consensus. The values of the correlation coefficient between various parameters related to Stellar, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 11, Fig. 6, and Eq. 13, respectively.

Table 11. Value of correlation coefficient between various metrics of Stellar

	*Open**	*High*	*Low*	*Close***	*Volume*	*Market Cap*
Open*	1					
High	0.99562	1				
Low	0.994952	0.992657	1			
Close**	0.992911	0.997789	0.994912	1		
Volume	0.687442	0.737221	0.668567	0.722975	1	
Market Cap	0.999358	0.994354	0.995187	0.992256	0.677702	1

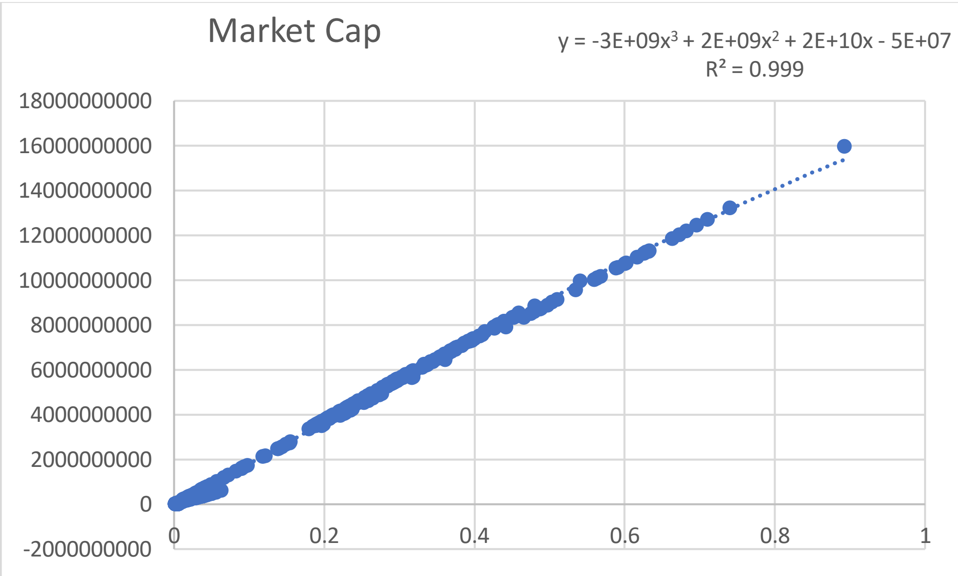

Fig. 6. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for Stellar

$$\text{Market\_Cap} = (-3E+09) *\text{Market\_Open}^3 + 2E+09*\text{Market\_Open}^2 + 2E+10*\text{Market\_open} - 5E+07. \quad (13)$$

5.7 Litecoin Results

Litecoin is a decentralized online currency fully compatible with the Bitcoin API, and therefore any application already offering Bitcoin can be easily integrated with Litecoin. Litecoin adopts the segregated witness, which corresponds to a soft fork change in the transaction format. The values of the correlation coefficient between various parameters related to Litecoin, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 13, Fig. 7, and Eq. 14, respectively.

Table 13. Value of correlation coefficient between various metrics of Litecoin

	Open*	High	Low	Close**	Volume	Market Cap
Open*	1					

High	0.996739	1				
Low	0.996541	0.995139	1			
Close**	0.995389	0.998844	0.996736	1		
Volume	0.75362	0.787107	0.742174	0.777827	1	
Market Cap	0.999732	0.996118	0.996677	0.995044	0.747772	1

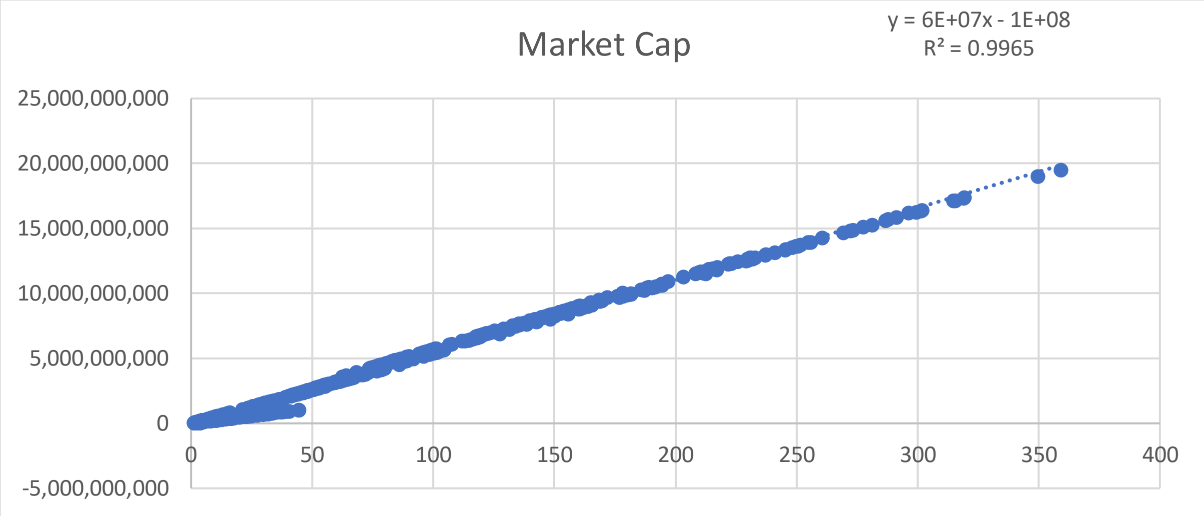

Fig. 7. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for Litecoin

$$Market\_Cap = 6E{+}07*Market\_Open - 1E{+}08. \qquad (14)$$

5.8 Cardano Results

Cardano is one of the first decentralized public blockchain cryptocurrency projects. It includes a number of best engineering practices, design principles, and avenues for further exploration [20]. It is the first blockchain platform to evolve from scientific philosophy and takes a research-first approach. The values of the correlation coefficient between various parameters related to Cardano, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 15, Fig. 8, and Eq. 15, respectively.

Table 15. Value of correlation coefficient between various metrics of Cardano

	Open*	High	Low	Close**	Volume	Market Cap
Open*	1					
High	0.988836	1				
Low	0.988851	0.98486	1			

Close**	0.984784	0.995444	0.989074	1		
Volume	0.58101	0.609473	0.546704	0.594108	1	
Market Cap	0.999999	0.98886	0.988888	0.984783	0.580825	1

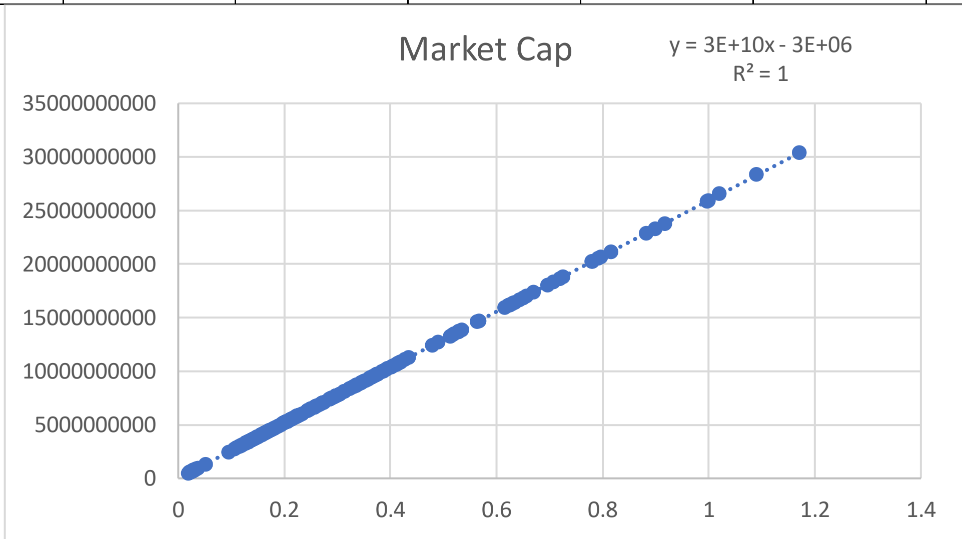

Fig. 8. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for Cardano

$$\text{Market\_Cap} = 3E{+}10{*}\text{Market\_Open} - 3E{+}06. \qquad (15)$$

5.9 Tether Results

Tether works on the blockchain with the Omni protocol. It changes cash into a digital currency such that there is always a 1-to-1 relationship between the traditional currency and Tether. Tether provides a transparent environment such that all Tether coins in circulation are the same as their reserves and these reserves are published daily after audits. It supports the US dollar, the Japanese yen, the Euro. The values of the correlation coefficient between various parameters related to Tether, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 17, Fig. 9, and Eq. 16, respectively.

Table 17. Value of correlation coefficient between various metrics of Tether

	*Open**	*High*	*Low*	*Close***	***Volume***	*Market Cap*
Open*	1					
High	0.876957	1				
Low	0.91595	0.714537	1			
Close**	0.957613	0.882951	0.908747	1		

Volume	0.059764	0.209793	-0.10591	0.062705	1	
Market Cap	0.040035	0.172837	-0.10287	0.042411	0.916161	1

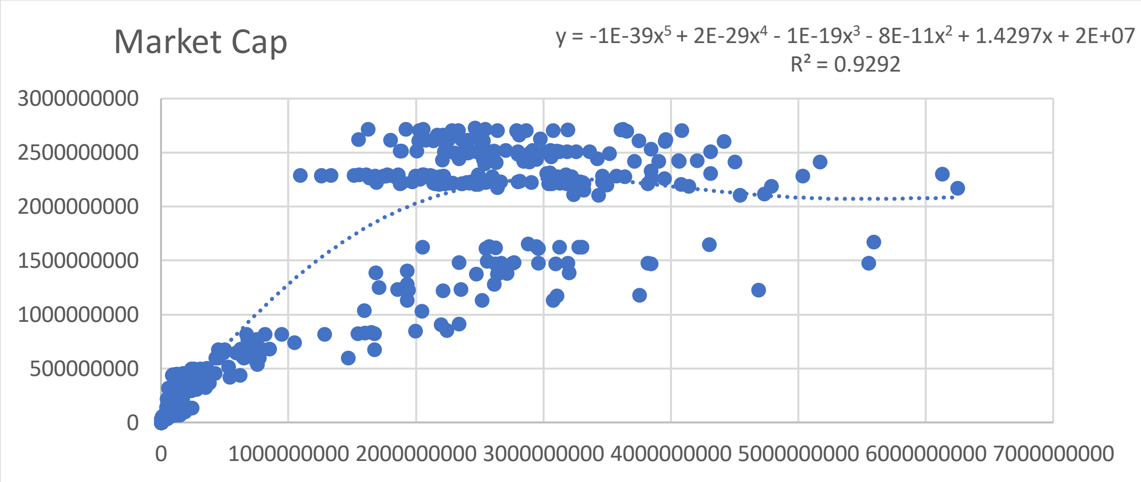

Fig. 9. Trendline and CCQ between Market Cap (y-axis) and Volume (x-axis) for Tether

$$\text{Market\_Cap} = (-1E\text{-}39) * \text{Volume}^5 + (2E\text{-}29) * \text{Volume}^4 - (1E\text{-}19) * \text{Volume}^3 - (8E\text{-}11) * \text{Volume}^2 + 1.4297 * \text{Volume} + 2E{+}07. \qquad (16)$$

5.10 TRON Results

TRON is a decentralized blockchain platform that makes use of a 3-layer architecture including the application layer, the core layer, and the storage layer. It uses a proof-of-stake (PoS) model that can handle 10,000 transactions per second, allowing users to create their own contracts. In addition, virtual machines are used for contracts, and its Delegated-Proof-of-Stake (DPOS) can handle future demand. The values of the correlation coefficient between various parameters related to Bitcoin, the trendline and the squared coefficient correlation, and the derived relationship between Market_Cap and the most dominating factor Market Open are presented in Table 19, Fig. 10, and Eq. 17, respectively.

Table 19. Value of correlation coefficient between various metrics of TRON

	*Open**	*High*	*Low*	*Close***	*Volume*	*Market Cap*
Open*	1					
High	0.9709	1				
Low	0.978489	0.95897	1			
Close**	0.960714	0.987127	0.971984	1		

Volume	0.739131	0.853606	0.723299	0.829522	1	
Market Cap	0.99997	0.970833	0.978633	0.960766	0.738884	1

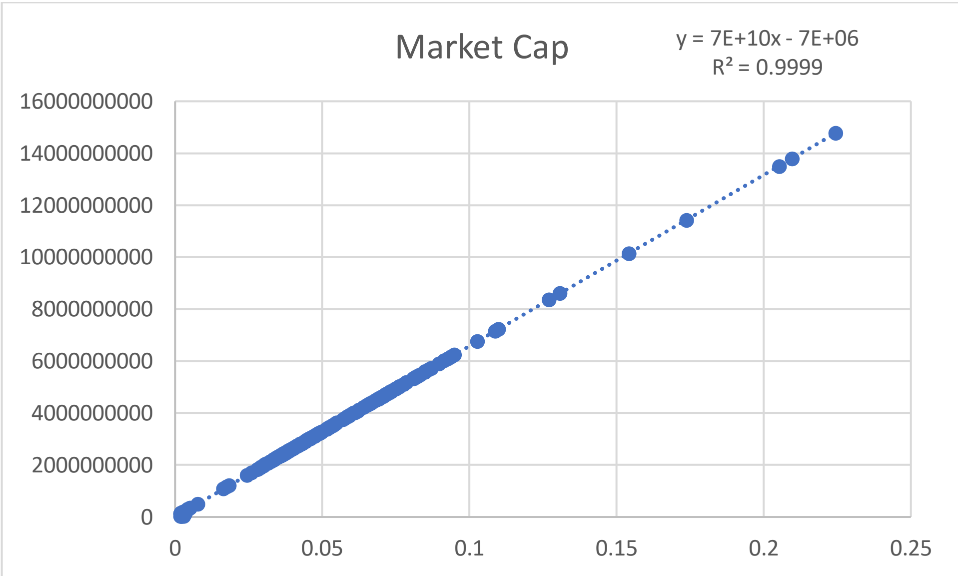

Fig. 10. Trendline and CCQ between Market Cap (y-axis) and Market Open (x-axis) for TRON

$$\text{Market\_Cap} = 7E{+}10 * \text{Market\_Open} - 7E{+}06. \qquad (17)$$

5.11 Visualization of Experimental Results Using Tableau

To find hidden patterns in variations of Market Cap and Market Open, this study uses a business analytics tool called Tableau, which is used to plot cryptocurrency trends shown in Fig. 11. Fig. 11 shows high fluctuations in the values of Market Cap and Market Open from November 2017 to January 2018.

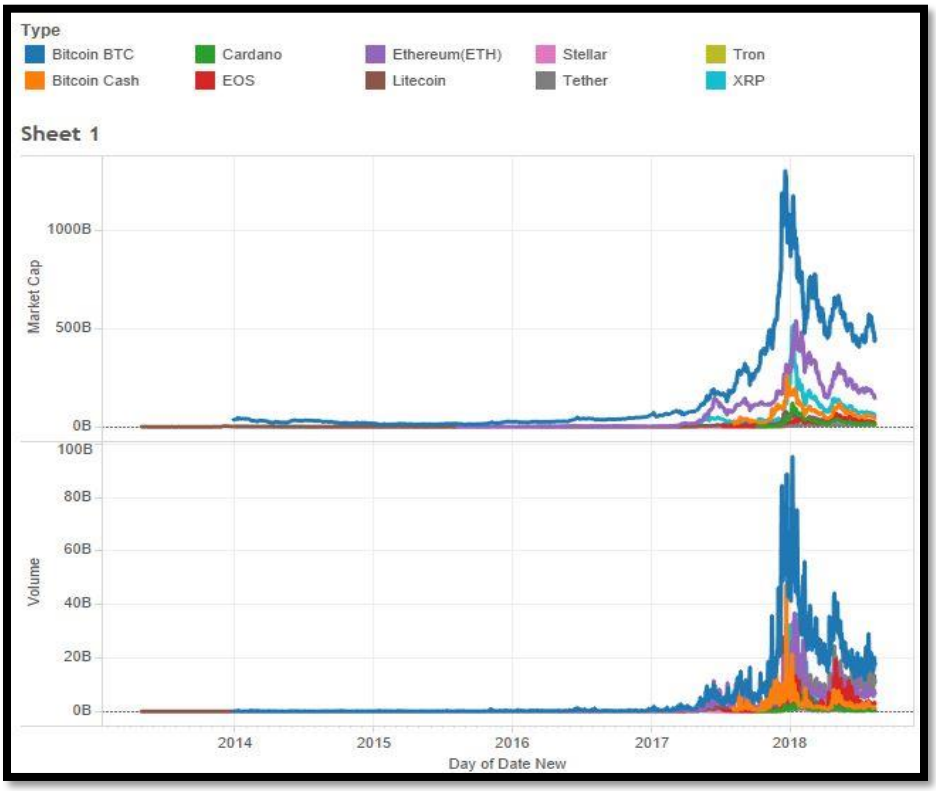

Fig. 11. Trends in Market_Cap and Market_open

5.12 Forecasting Future Cryptocurrency Values

This set of experiments forecasts future cryptocurrency values using the exponential smoothing method based on previous values for Tether and Stellar. This section presents expected future trends for these cryptocurrencies.

Forecasting Tether

Fig. 12 shows various fluctuations in parameters for Tether for the given time interval. Fig. 13 shows actual and forecasted values of Market Cap for Tether. Fig. 14 shows lower and upper confidence boundaries for forecasted values of Market Cap for Tether. Table 21 shows various errors in forecasted values.

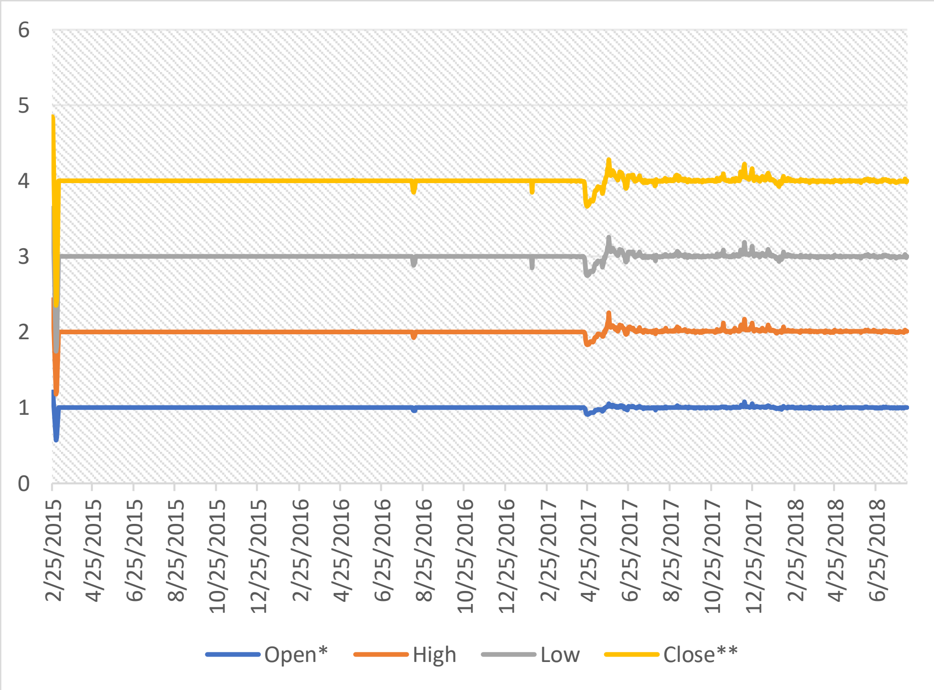

Fig. 12. Variations in parameters for Tether

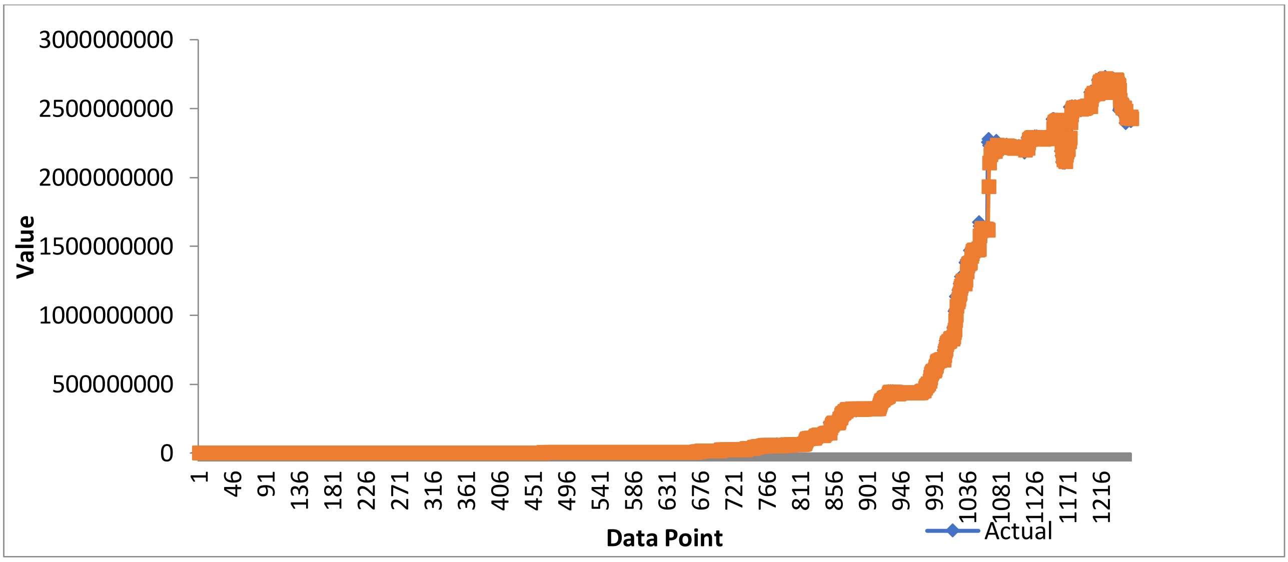

Fig. 13. Actual and forecasted values of Market Cap for Tether

Fig. 14. Lower and upper confidence boundaries for forecasted value of Market Cap for Tether

Table 21. Values of error measures in forecasted values for Tether

Statistic	Value
Alpha	0.83
MASE	24.07
SMAPE	0.01
MAE	2,53,71,092.70
RMSE	5,41,32,447.31

Forecasting Stellar

Fig. 15 shows lower and upper confidence boundaries for forecasted values of Market Cap for Stellar. Table 22 shows various errors in forecasted values.

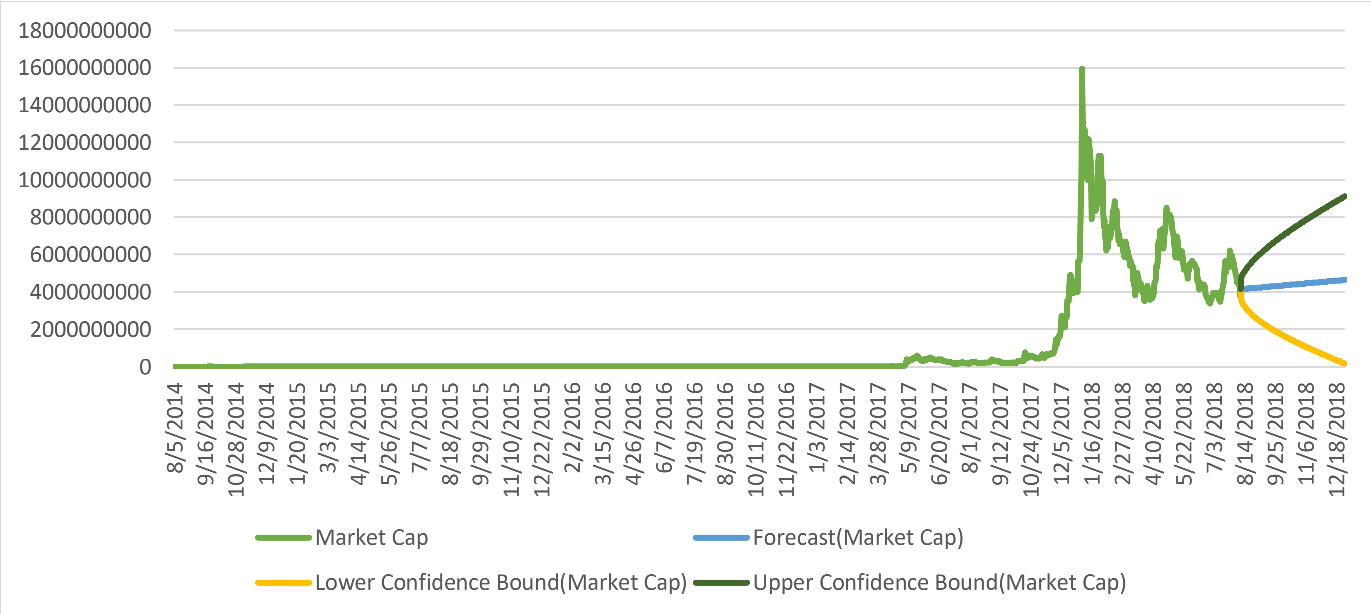

Fig. 15. Lower and upper confidence boundaries for forecasted value of Market Cap for Stellar

Table 22. Values of error measures in forecasted values for Steller

Statistic	Value
Alpha	0.50
MASE	92.06
SMAPE	0.08
MAE	41,73,99,715.12
RMSE	73,82,37,249.51

6. Conclusions and Future Scope

The decentralization of cryptocurrencies through technological innovation is weakening government control over currencies, making them an important research topic. This study explores cryptocurrencies and their recent trends and analyzes correlations using various metrics. An analytics tool called Tableau is used to visualize analysis results for deeper insights into cryptocurrencies. For Bitcoin, Litecoin, Cardano, and TRON, their Market_Cap value is linearly correlated with Market_Open. There is a quadratic relationship for Ethereum, Ripple, Bitcoin Cash, EOS, Stellar, and Tether. For Tether, Market_Cap has a quadratic relationship with Volume, and for EOS, Market_Cap has a quadratic relationship with Market_Low. Future cryptocurrency values are forecasted using the exponential smoothing method based on historical values.

Since cryptocurrency values also depend on diverse factors such as country-specific rules, political pressures, and the media, future research should consider such factors and also explore the blockchain concept using neural networks for deeper and more precise results.

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