Forecasting Cryptocurrency Investment Return Using Time Series and Monte Carlo Simulation

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Abstract. *Cryptocurrencies are attracting significant amount of attention. Everything started with Bitcoin and built up to the situation where we have over 1500 cryptocurrencies. One can say that cryptocurrency market is the new stock market. This market is still highly volatile, but decentralized, open, and widely accessible. In this paper we will use time series analysis and Monte Carlo simulation for forecasting cryptocurrencies' return for selected time period. With huge price oscillations present it is hard to provide precise return predictions, but any step towards analysing cryptocurrencies adds to understanding the market.*

Keywords. cryptocurrency, return on investment, time series, simulation, model, Monte Carlo simulation

1 Introduction

Cryptocurrencies can be defined as digital, computer currencies whose implementation stands on the principles of cryptography, both to validate the realised transactions and to enlarge the currency in circulation (Cocco, Concas, & Marchesi, 2017).

Bitcoin is seen as the first decentralized digital currency platform, a currency without central authority to regulate it's usage, validate and settle transactions (Gandal & Halaburda, 2016). It was introduced in 2009, but only recently it's value and popularity has significantly grown. Although newer cryptocurrencies gained popularity much faster, Bitcoin (BTC) is still the one with highest market valuation, usage, merchant acceptance and popularity (Hayes, 2015).

Following Bitcoin's footsteps, other cryptocurrencies were launched (Iwamura, Kitamura, & Matsumoto, 2014). It should be noted that anyone can create its own cryptocurrency in minutes (Long, 2018). Popular name for all cryptocurrencies released after Bitcoin is *altcoins*. Some of the most popular altcoins are Ethereum (ETH), Ripple (XRP), EOS, Litecoin (LTC), Zcash (ZEC), and Monero (XMR).

In scientific literature Bitcoin is the most studied cryptocurrency. Barber, Boyen, Shi, and Uzun (2012) pointed to several problems with Bitcoin, such as technical vulnerability, potential deflationary spiral, accidental loss of bitcoins, and malware attacks. Urquhart (2016) showed that Bitcoin market returns are significantly inefficient if observed at once, on the whole sample, but when sample is split into two subsample periods, tests indicate that Bitcoin is efficient in the latter period. Yermack (2013) analysed Bitcoin price against fiat currencies and showed that its volatility undermines its usefulness as a currency. Baek and Elbeck (2015) presented strong evidence to suggest that Bitcoin volatility is internally (buyer and seller) driven – leading to the conclusion that the Bitcoin market is highly speculative. Cheah and Fry concluded that Bitcoin price is prone to speculative bubbles and that the market is highly volatile (2015b; 2016). Bitcoin showed vast success and popularity since its creation (more in the recent years), thanks to its added value (Marian, 2013). Namely, some of the most important pros of Bitcoin are anonymity, decentralised nature, enhanced revenue, and use of proof-of-work mechanisms (Moore & Christin, 2013).

Cryptocurrencies have recently become a topic of interest for scientific papers. Only 193 articles have been published by the end of 2017 in journals indexed on Clarivate Analytics Web of Science Social Sciences Citation Index (SSCI) and Science Citation Index Expanded (SCIE) with the topic "cryptocurrency" OR "bitcoin" (Clarivate Analytics, 2018; Zornić & Marković, 2018).

Most of the authors tried to determine factors influencing cryptocurrency price, trade volume, and volatility. For example, Sovbetov (2018) examined factors that influence prices of cryptocurrencies such as Bitcoin, Ethereum, Dash, Litecoin, and Monero. Those factors include cryptomarket-related factors and attractiveness of cryptocurrencies in long-run.

Glaser, Zimmermann, Haferkorn, Weber, and Siering (2014) showed that most of the interest in cryptocurrencies on Wikipedia is due to the cryptocurrencies' investment asset aspect and not due to the usage as currency itself. When cryptocurrencies become widely usable for their primary purpose – as medium of exchange for goods and services, they will be even more interesting to analyse (Zornić & Marković, 2018). Concept of purely digital currency will highly increase convenience of payments in digital world, but at the moment their usage involves high risk. Regardless digital wallet security risk, currently the highest is risk related to cryptocurrency value due to its instability.

Aim of this paper is to provide a model for cryptocurrency return analysis using a combination of two well-known methods, time series analysis and Monte Carlo simulation, using widely accessible data source. This paper is organized as follows. Firstly, the cryptocurrency is defined and short literature review is presented. Afterwards, descriptive statistics of collected cryptocurrencies' price data is displayed, followed by time series fit functions. Those time series fit functions are used as input for Monte Carlo simulation, whose results are analysed afterwards. Finally, in the last section, concluding remarks and future directions of the research are provided.

2 Model for Forecasting Cryptocurrency Investment Return

Five cryptocurrencies with highest market capitalization on 29th of June 2018 have been chosen for building the model for forecasting cryptocurrency investment return: Bitcoin ($108.88 B), Ethereum ($45.64 B), Ripple ($17.67 B), EOS ($8.06 B), and Litecoin ($ 4.58 B). Data has been collected for the daily closing price in USD ($) for each of them. Data for all cryptocurrencies except for EOS covers the period from 01.01.2016 to 29.06.2018 (CryptoCompare, 2018a, 2018c, 2018e, 2018d), and the period from 29.06.2017. to 29.06.2018. for EOS (CryptoCompare, 2018b). There are a lot of online cryptocurrency historical price databases, but CryptoCompare is selected as the one that has prices for all the mentioned cryptocurrencies. Simple descriptive overview of the prices and natural logarithm of daily returns is presented in Table 1.

We can see that Bitcoin price has grown from an average of $567.00 in 2016 to $9131.34 in 2018. The rate has been even higher for some periods of time, reaching the maximum value of $19,345.49 on 16.12.2017. Other cryptocurrencies saw excessive growth in value, too. Ripple had the highest mean daily return of 1.57% in 2017. Other cryptocurrencies had their highest mean daily return in the same year, too.

Table 1. Cryptocurrency prices and daily return

		2016			2017			2018		
		Days	**Mean**	Std. Dev.	Days	**Mean**	Std. Dev.	Days	**Mean**	Std. Dev.
Bitcoin	**Price [$]**	366	**567.00**	138.35	365	**3981.07**	3987.18	180	**9131.34**	2288.07
	Daily return [%]		**0.22**	2.58		**0.73**	4.91		**-0.47**	5.11
Ethereum	**Price [$]**	366	**9.76**	3.67	365	**221.68**	183.80	180	**717.69**	232.40
	Daily return [%]		**0.59**	7.25		**1.24**	6.88		**-0.32**	6.09
Ripple	**Price [$]**	366	**0.01**	0.00	365	**0.20**	0.25	180	**0.90**	0.48
	Daily return [%]		**0.05**	5.76		**1.57**	11.52		**-0.84**	7.42
EOS	**Price [$]**				186	**2.22**	2.35	180	**10.41**	3.59
	Daily return [%]					**1.19**	13.35		**-0.03**	9.33
Litecoin	**Price [$]**	366	**3.76**	0.47	365	**49.85**	64.13	180	**157.09**	44.86
	Daily return [%]		**0.06**	2.78		**1.08**	8.12		**-0.62**	6.35

Time series analysis and Monte Carlo simulation is conducted using Palisade @RISK 7.5.2 plugin software for Microsoft Office Excel. Total of 11 time series algorithms have been employed for each cryptocurrencies' return. @RISK features automatic detection of required transformations to achieve time series stationarity. Akaike Fit (Akaike information criterion – AIC) and Bayesian Fit (Bayesian information criterion – BIC) are used as quality measures for time series fit. Results for the best ranked algorithms for each cryptocurrency are presented in Table 2. In addition to fitting time series data with appropriate model, forecasting for seven days is done. These fitting results are used as input for Monte Carlo simulation

Table 2. Time series fit details

Cryptocurrency [type]	Bitcoin return [MA1]	Ethereum return [MA1]	Ripple return [GARCH]	EOS return [MA1]	Litecoin return [MA1]
Data Transform	Auto Detect	Auto Detect	Auto Detect	Auto Detect	Auto Detect
Function	None	None	None	None	None
Detrend	None	None	None	First Order	None
Deseasonalize	None	None	None	None	None
Seasonal Period	N/A	N/A	N/A	N/A	N/A
Akaike (AIC) Rank	#1	#1	#1	#1	#1
Akaike (AIC) Fit	-3187.55	-2283.47	-2157.93	-527.64	-2493.80
Bayesian (BIC) Rank	#1	#1	#1	#1	#1
Bayesian (BIC) Fit	-3.19E+03	-2.28E+03	-2.14E+03	-5.28E+02	-2.49E+03
Parameters	3	3	4	3	3
Parameter #1	Mu	Mu	Mu	Mu	Mu
Value	0.002869743	0.006715739	0.004815913	-0.00022336	0.00335444
Parameter #2	Sigma	Sigma	Omega	Sigma	Sigma
Value	0.042167778	0.068930561	0.003604131	0.116822606	0.061950577
Parameter #3	B1	B1	A	B1	B1
Value	0.003730151	0.009485065	0.988957199	-0.934305919	0.022356184
Parameter #4			B		
Value			0.043549253		

Graphs with best time series fit functions, including historical data and 7-days prediction period are presented on Figures 1-5. The *x-axis* represents time, where 0 is data of data collection (29.06.2018) and the *y-axis* represents daily return. These functions and parameters will be used for creating financial model for cryptocurrency return analyses.

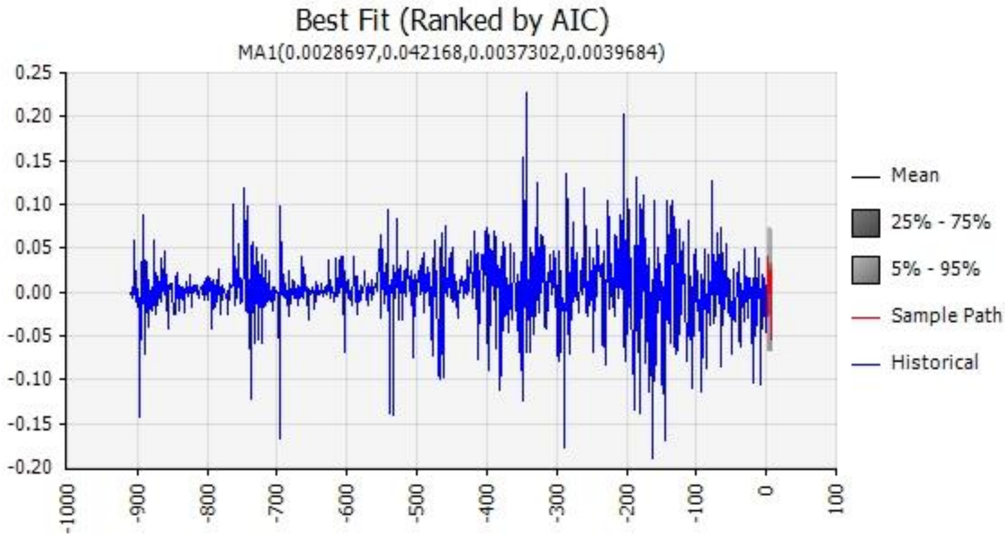

Figure 1. MA1 time series for Bitcoin daily returns

Figure 1 presents time series for Bitcoin daily returns. As we can see from historical data, oscillations are high, from -18.92% (16.01.2018 - t_{-164}) to 22.76% (20.07.2017 - t_{-344}). In the last 30 days, there were two peaks with return less than -10%. The 90% confidence interval for daily return in the future 7 days will be between -6.65% and 7.23%.

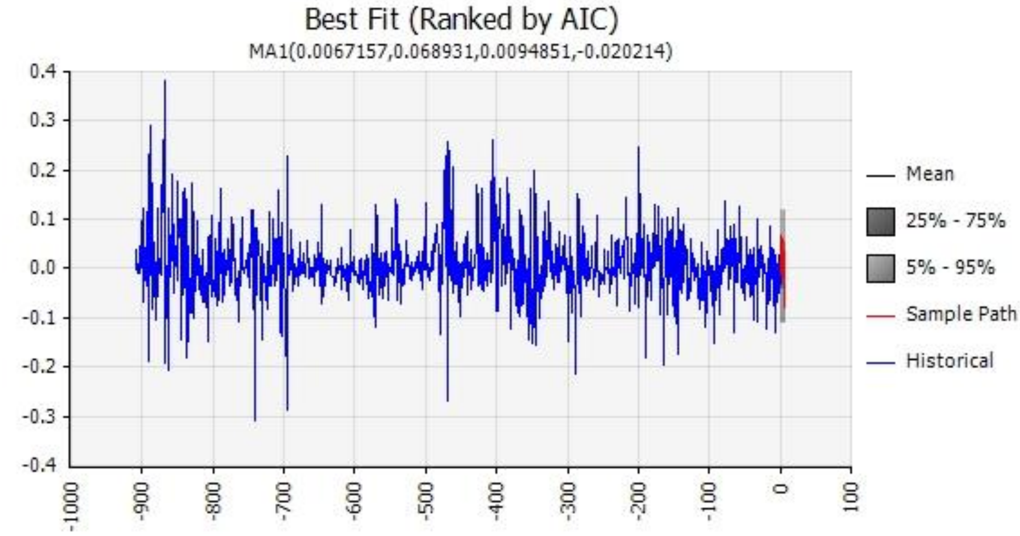

Figure 2. MA1 time series for Ethereum daily returns

Ethereum had even higher return peaks. As we can see from Figure 2, there are periods with high oscillations, from -31.01% (18.06.2016 - t_{-741}) to 38.30% (11.02.2016 - t_{-869}). The 90% confidence interval for daily return in the future 7 days will be between -10.7% and 12.00%.

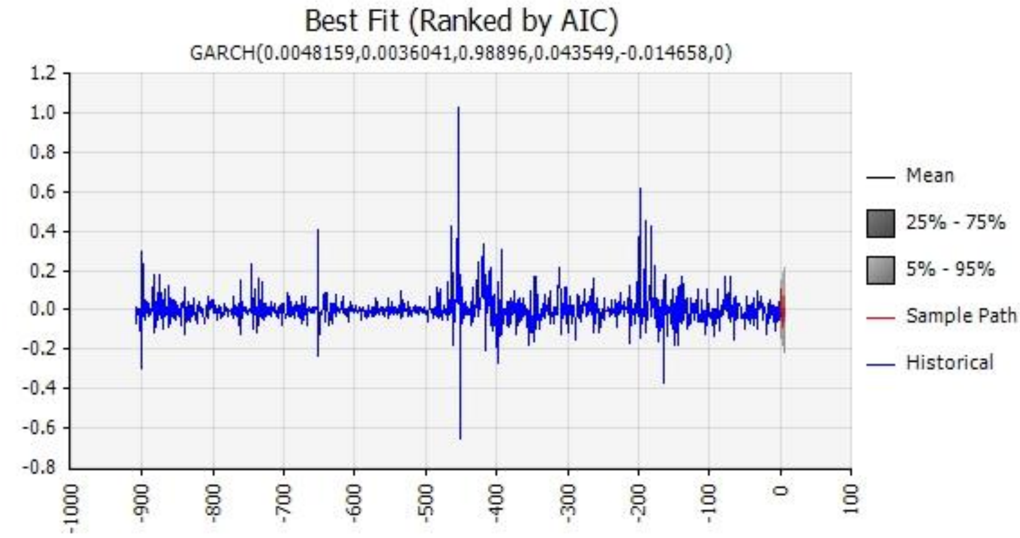

Figure 3. GARCH time series for Ripple daily returns

Ripple return had had one of the largest peaks of observed cryptocurrencies. Analysing Figure 3, we can see high peaks, from -65.30% (03.04.2017 - t_{-452}) to 102.80% (02.04.2017 - t_{-453}). The 90% confidence interval for daily return in the future 7 days will be between -20.00% and 21.00%.

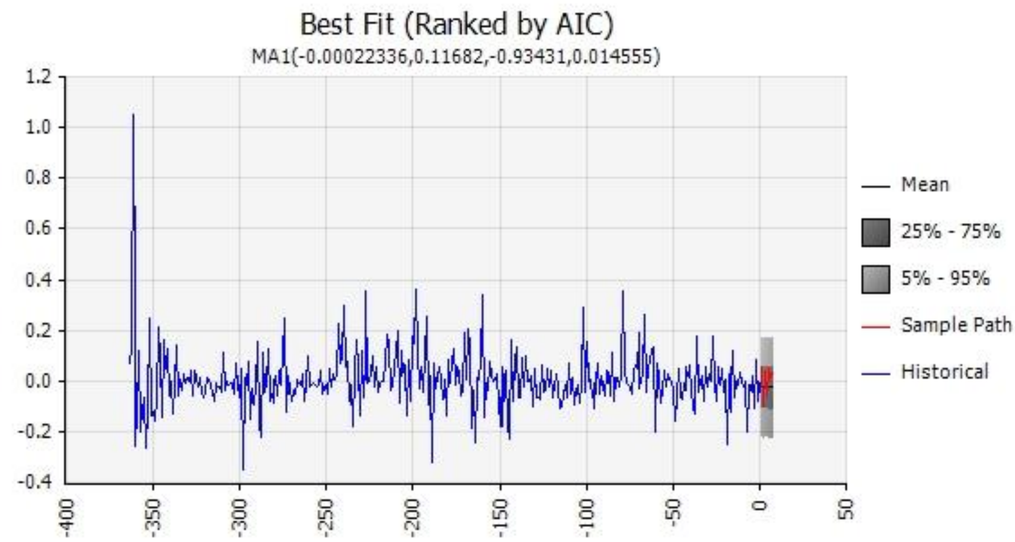

Figure 4. MA1 time series for EOS daily returns

Figure 4 presents time series for EOS daily return. Highest daily return of 104.98% was achieved 02.07.2017 - t_{-298}. On the other side, the highest decrease in value of -35.21% was achieved 04.09.2017 - t_{-362}. The 90% confidence interval for daily return in the future 7 days will be between -22.00% and 16.90%.

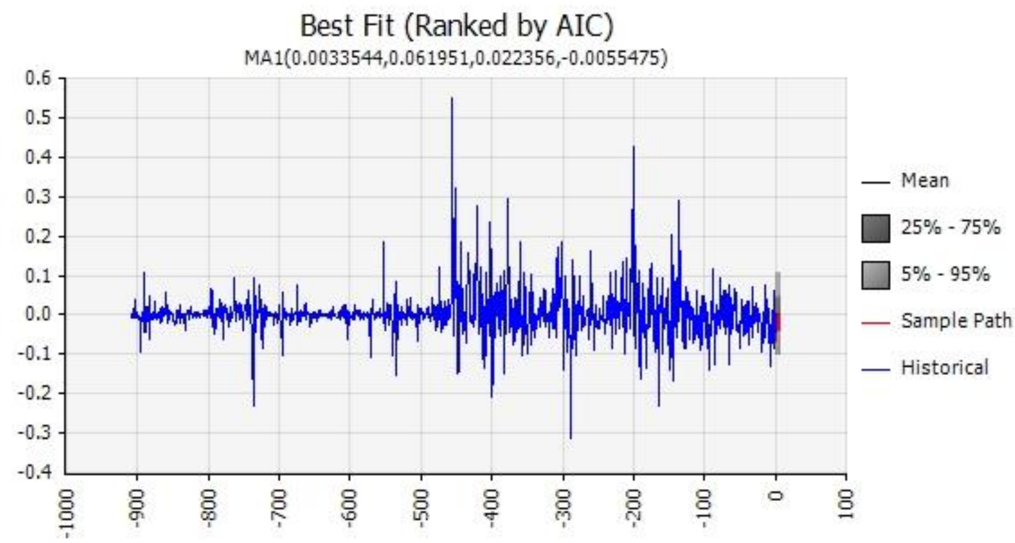

Figure 5. MA1 time series for Litecoin daily returns

Litecoin daily return time series is presented in Figure 5. Analysing time series, we can see that return is oscillating from -31.25% (14.09.2017 - t_{-288}) to 55.16% (30.03.2017 - t_{-456}). The 90% confidence interval for daily return in the future 7 days will be between -9.90% and 10.50%.

Figure 6 presents the Monte Carlo model in Microsoft Office Excel. Yellow fields are for input variables, blue for calculation, and green for output. Five different time series functions are used for calculating 7-days return and based on the results each cryptocurrencies' price is calculated.

Monte Carlo simulation was run using @RISK software with 100.000 iterations. Cryptocurrencies' return is generated using specific time series function in each iteration and afterwards other values are calculated and iteration results are saved in database. Those results are presented in form of probability distributions together with excessive statistical indicators.

Cryptocurrency	Price [29.06.2018]	Price [06.07.2018]	Ln(return)
Bitcoin	$ 5,910.5100	$ 6,030.5132	2.01%
Ethereum	$ 414.8600	$ 434.7369	4.68%
Ripple	$ 0.4402	$ 0.4551	3.32%
EOS	$ 7.3000	$ 6.1115	-17.77%
Litecoin	$ 73.8800	$ 75.6292	2.34%

=D4/B4

=EXP(D2)*B2

Time series functions

Figure 6. Predicted cryptocurrency 7-days returns

One can say that investment into cryptocurrencies carries high risk, as the market is highly volatile (Yermack, 2013). On the other side, potential profits are significant. Our results presented on Figures 7-11 confirm these claims. Based on our results, Ethereum showed the highest mean return and Bitcoin lowest standard deviation.

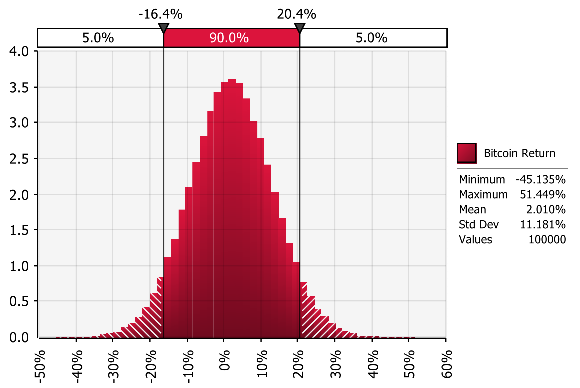

Figure 7. Bitcoin return

Average return on Bitcoin (Figure 7) for 7-days period is 2.01% with standard deviation 11.18%.

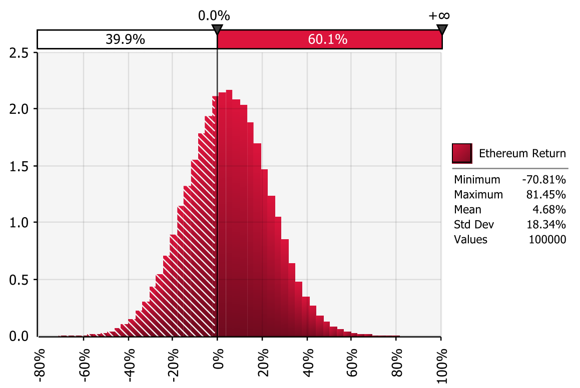

Figure 8. Ethereum return

Average return on Ethereum (Figure 8) for 7-days period is 4.68% with standard deviation 18.34%. Maximal predicted return in this period is 81.45%, and on the other side, minimal -70.81%. From the same figure we can also see the probability that profit will be achieved (60.1%).

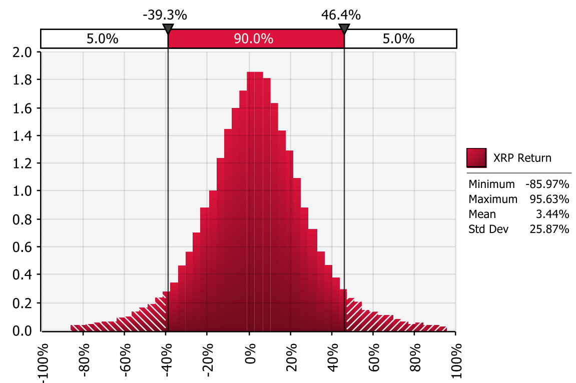

Figure 9. Ripple return

Ripple 7-days period mean return is 3.44% with standard deviation 25.87% (Figure 9).

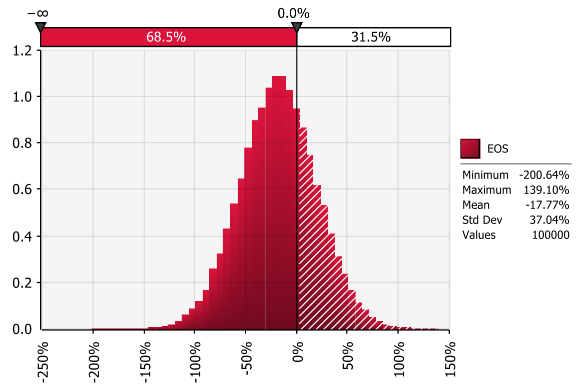

Figure 10. EOS return

EOS showed the worst result, when return on investment is observed (Figure 10). Mean return is negative (-17.77%) with standard deviation 37.04%. Probability of losing money when investing in EOS is 68.5%.

Litecoin has the second-best standard deviation – 16.76% and average return for 7-days period 2.34% (Figure 11).

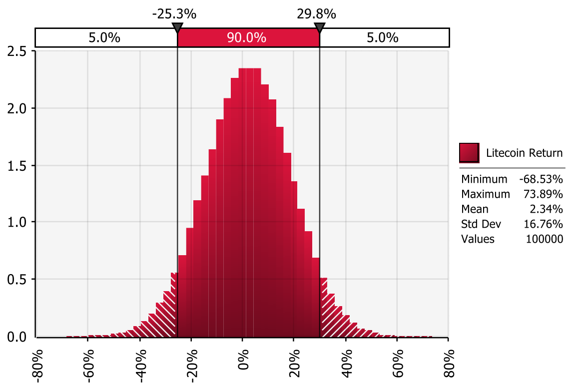

Figure 11. Litecoin return

3 Conclusion

Aim of this paper was to provide a model for cryptocurrency return analysis using a combination of two well-known methods, time series analysis and Monte Carlo simulation. Additionally, popular cryptocurrency price tracker, CryptoCompare, was used as data source.

Five cryptocurrencies were included in analysis: Bitcoin, Ethereum, Ripple, EOS, and Litecoin. Time series model was fitted for each of them and resulting @RISK functions are used as input for Monte Carlo simulation. Monte Carlo simulation results for observed cryptocurrencies show high investment risk, but also high potential profits. Based on results, all cryptocurrencies except EOS have positive mean return.

Unfortunately, we already concluded that Bitcoin price is prone to speculative bubbles and that the market is highly volatile. This means that it is currently not possible to give precise return and profit predictions based on scientific methods. Regardless, any kind of information gathering and analysis are giving higher insight into possible price trends. Provided model gives possibility to analyse results in terms of probabilities and statistical indicators.

During the research, several future directions of the study emerged. Firstly, more cryptocurrencies can be included in the analysis, especially the newly created and fast-rising ones. The other direction is including portfolio optimization features.

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