International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

Stability of Cryptocurrency Using Machine Learning Algorithm

***Homedeep Singh Saggu* [1], *Mr Manoj R* [2], *Anmol Singh Gill* [3]**

[1] Department of Computer & Communication Engineering
Manipal University Jaipur
Jaipur, 303007, India
[2] Department of Computer Science & Engineering
Manipal Institute of Technology, Manipal
Manipal Academy of Higher Education
Manipal, 576104, India
[3] Department of Computer Science & Engineering
Manipal University Jaipur
Jaipur, 303007, India

E-mail address: homedeep.209303175@muj.manipal.edu , manoj.r@manipal.edu , anmol.219301645@muj.manipal.edu

Received ## Mon. 20##, Revised ## Mon. 20##, Accepted ## Mon. 20##, Published ## Mon. 20##

Abstract: – The acceptance of cryptocurrencies as a medium of exchange has long been hindered by the volatility of their pricing. In this study, we investigate the utility of rebasing as a tool for maintaining bitcoin prices. To achieve price stability, we present a mathematical method with use of machine learning algorithm that periodically modifies the total supply of the cryptocurrency based on a selected benchmark. By modelling several market circumstances, we assess the performance of our suggested rebasing strategy and compare it to other price stabilisation techniques already in use. Our research demonstrates that rebasing can successfully control a cryptocurrency's price while preserving the integrity of its decentralised architecture. However, we also point out significant restrictions and difficulties in putting rebasing rules into practise, such as potential manipulation concerns and the requirement for community agreement. Our research adds to the ongoing discussion over whether cryptocurrencies are a practical form of exchange and offers guidance to investors, policymakers, and cryptocurrency enthusiasts.
In contrast to conventional cryptocurrencies like Bitcoin or Ethereum, which are renowned for their extreme volatility, stable cryptocurrencies aim to offer a more dependable and predictable store of value. Stablecoins are frequently employed as a store of wealth, a payment method, or a hedge against swings in the cryptocurrency market. There are many ways artificial intelligence (AI) can be applied to improve the stability of cryptocurrencies. Algorithmic modifications to the money supply are one of the keyways that stablecoins use AI.

Keywords: – *Machine Learning algorithm, Logistic Regression, LSTM (long short term memory), Cryptocurrency, Artificial Intelligence, Rebasing.*

I. Introduction

A stable cryptocurrency is a type of digital currency that is designed to maintain a stable value. The value of a stable cryptocurrency is intended to remain stable in relation to another asset or currency, typically the US dollar. This can be done in a number of ways, including by tying the value of the cryptocurrency to a fiat currency or a basket of assets, utilising smart contracts to keep prices stable, or changing the money supply according to an algorithm.

Cryptocurrencies, with their decentralized architecture and promises of financial freedom, have attracted considerable attention in recent years. However, the volatility of cryptocurrency prices has remained a significant challenge for their adoption as a medium of exchange. Fluctuating prices hinder their usefulness for everyday transactions, making them more suitable for investment and trading activities rather them, being use as a medium of transaction in day to day life. This has not only resulted them in being consider as an illegal investment source and unaccounted but also let to banning of cryptocurrency in some countries. In this study, we propose a new method to stabilize the price of a cryptocurrency using a mathematical formula called "rebasing" and Machine Learning Algorithm. The rebasing technique involves adjusting the total supply of a cryptocurrency periodically, based on a chosen benchmark/value, to maintain price stability. Specifically, if the

E-mail: manoj.r@manipal.edu

price of the cryptocurrency goes up by a certain percentage, then additional coins are minted/created, and if the price goes down by the same percentage, then coins are burned/removed. This process helps to regulate the supply of cryptocurrency and maintain its value. In this research paper, we explore the potential of rebasing as a means of stabilizing the price of a cryptocurrency and automate it using machine learning. We provide a detailed explanation of the rebasing method, including its mathematical formula and implementation guidelines. Furthermore, we evaluate the effectiveness of our proposed rebasing technique by simulating different market scenarios and comparing it with existing price stabilization methods. While using rebasing shows promising results in stabilizing the price of a cryptocurrency, there are also limitations and challenges to its implementation. We discuss these limitations and propose ways to address them to ensure the stability and integrity of cryptocurrency. Our study contributes to the ongoing debate on the feasibility of cryptocurrencies as a practical medium of exchange and provides insights for policymakers, investors, and cryptocurrency enthusiasts.

II. Literature Review

[1] According to this report, Terra's failure emphasises the significance of stablecoin design and risk management, particularly considering stablecoins rising popularity. Future stablecoin designs, according to the authors, ought to think about diversifying their anchor assets, putting risk management plans into place, and improving liquidity. In order to safeguard customers and guarantee the stability of financial institutions, the paper also emphasises the necessity of regulatory control of stablecoins.

[2] The authors point out that whereas stablecoins using cryptocurrency as collateral, such as Dai, suffer the risk of collateral volatility, stablecoins using fiat money as collateral, such as Tether and USD Coin, face the risk of bank runs. According to the article, stablecoins that have many types of collateral or procedures to control collateral risk may be more stable than those that only have one sort of collateral.

[3] The article talks about the market sentiment, supply and demand, and technological advancements that affect cryptocurrency value. The authors also look at how cryptocurrencies have performed over time, emphasising the considerable volatility and risk attached to these assets.

[4] The authors look at the advantages of stablecoins, including less volatility and easier access to digital assets, as well as the drawbacks, like market risks and regulatory issues. The various kinds of stablecoins including those backed by money, commodities, and algorithms are covered in the article. The authors examine the techniques stablecoins employ to keep their value stable, such tying them to fiat money or adjusting the coin supply through an algorithm. The article also discusses stablecoins possible effects on the financial system, including its use in international transactions and as a medium of exchange for goods and services.

[5] The Basis protocol, which is intended to establish a price-stable cryptocurrency unlinked from any particular asset or currency, is presented in the article. According to the authors, to maintain a constant value, the Basis protocol uses an algorithmic central bank that modifies the supply of Basis tokens in response to variations in demand. The three different forms of Basis tokens—Basis, Base Shares, and Base Bonds are discussed in the article, along with how they interact to keep Basis tokens' values consistent. According to the authors, the Basis protocol employs a "bond auction" mechanism to encourage users to sell Basis tokens when their price is higher than their desired value and to acquire them when it is lower.

[6] The authors contend that several variables, including the stablecoin mechanism's design, the quality and liquidity of the underlying assets, market expectations and confidence in the stability of the stablecoin, affect the stability of stablecoins. The article discusses the many stablecoin varieties, including fiat-backed, commodity-backed, and algorithmic stablecoins, as well as how their stabilising methods work. The authors examine the effects of market factors, such as shifts in stablecoin supply and demand and outside shocks, on the stability of stablecoins and suggest that market factors may put that stability in jeopardy. The function of governance and regulation in preserving stability is covered in the article, along with the necessity of open, efficient governance institutions and regulatory supervision.

[7] The authors use a collection of historical cryptocurrency price data to analyse the data and forecast future prices using AI techniques like support vector regression (SVR) and long short-term memory (LSTM) neural networks. The authors compare their approach to other approaches like linear regression and autoregressive integrated moving average (ARIMA) models in order to assess the performance of their methodology using various measures, such as mean absolute error (MAE) and root mean squared error (RMSE). The volatility and unpredictability of cryptocurrency markets, the necessity for high-quality data, and the proper feature selection are discussed as constraints and difficulties of utilising AI for cryptocurrency price analysis.

[8] The paper lists a number of obstacles to adopting AI for cryptocurrencies, including issues with data quality and availability, legal and regulatory concerns, and the possibility that AI would worsen already-existing biases and inequalities in the cryptocurrency industry. The authors also go into the ethical ramifications of utilising AI in cryptocurrency,

including the need for accountability and transparency as well as the dangers of AI-driven market manipulation and other types of bad behaviour.

[9] The authors assess how well several machine learning (ML) models, such as support vector machines and artificial neural networks, forecast the price of Bitcoin and other cryptocurrencies. The paper lists several variables, including data quality and availability, the choice of input features, and the dynamic and unpredictable nature of cryptocurrency markets, that may have an impact on how accurate ML-based price forecasts are. The potential for overfitting and the likelihood of model failure during periods of excessive market volatility are only a few of the hazards and restrictions that the authors mention when talking about using ML-based trading techniques.

III. Research Methodology

A. Formula applied and the limitations to the rules

The Formula applied to stabilize the value of the stable cryptocurrency is "Rebasing" [5] which means that with the increase in demand the supply (number of coins) is increased and for decrease in demand the supply is decreased. This helps us to stabilize the value of the cryptocurrency at that interval of time.

The formula applied to know the change in value-

- For increase in value of the coin

$$Z = X + (Y\% \text{ of } X) \tag{1}$$

- For decrease in the value of the coin

$$Z = X - (Y\% \text{ of } X) \tag{2}$$

Where,
Z = The output value of the coin after percentage change
X = The value (Stable) of the coin before Rebasing
Y = The percentage change in the value of the coin (it can be both negative or positive)

The formula to know the change in number of coins (after the change in value of coin)-

$$H = \frac{Z}{X} \tag{3}$$

Where,
H = Number of new coins after rebasing
X = The value (Stable) of the coin before Rebasing
Z = The output value of the coin after performing Rebasing

Set of rules alongside the rebasing to ensure an extra security to keep the currency stabilize-

- The currency will be valued through [4] a mix of Collateralized and Algorithmic techniques, that is it will be a Hybrid Currency [2] as this allows us to minimise the disadvantages of both the techniques and get the advantages of both techniques. (The advantages and disadvantages are shown in result section.)
- The initial value of the coin can be determined anything as per need. In our case, we decided the value to be 30,000/- with a supply of 1,00,000 coins (Large number of coins are to be taken to further minimise the volatility cause due to high trade volume) in the market.
- Trading stops whenever the value of the currency goes beyond the range of $\pm$1.5% of its stated value on that day or at the interval. [1]
- Even if the value does not change to about 1.5% upside or downside, Rebasing will be performed after every 50 minutes (the 50 minutes time is not a strict constraint , but in our algorithmic run of the model we took 50 minutes).[3]
- Whenever the transaction is supposed to be done "the number of coins (H)" will be changed as per the current value of the cryptocurrency.
- The objective is to use it as a stable alternative to keep the value of a volatile assert stable.[6]

B. Machine Learning Classifiers

This section discusses about the machine learning algorithms which are applied on the dataset taken. Time series analysis is a typical method used in machine learning to forecast whether a value will increase or decrease. A statistical method called time series analysis makes use of previous data to spot trends and patterns throughout time, and then it uses those trends to estimate future values. Hence, using Long Short-Term Memory Algorithm that is designed to handle time series data can learn long-term dependency. So, by using two algorithms one to identify if the value is down or up and the other to predict the output after applying rebasing.[7]

C. Reasons

The reason of using Long Short-Term Memory (LSTM) networks because they can retain information from previous data points and use it to forecast future values, making them suitable for handling the sequential nature of time series data such as cryptocurrency price prediction.[8] They can capture long-term dependencies and patterns in the data, which is crucial for accurate predictions in financial time series. Studies have demonstrated that LSTMs can achieve significant reductions in error rates compared to more traditional Autoregressive Integrated Moving Average (ARIMA) algorithm, making them a more reliable choice for financial time series prediction Numerous studies have successfully applied LSTM models to predict stock prices, cryptocurrency prices, and other financial time series. It's crucial to keep in mind that these methods are not infallible and ought to be used in conjunction with other information and analysis.[9]

D. Data applied

- Input Data:

  Increase in value (positive percentage change)-
  Let the value of each coin be 30,000/- & the change in value is in range of 0.1% - 1.5%

Set	X (Value Before Rebase)	Y (Percentage Change)	Z (Value After Rebase)
1	30000	0.10%	30030.00
2	30000	0.20%	30060.00
3	30000	0.30%	30090.00
4	30000	0.40%	30120.00
5	30000	0.50%	30150.00
6	30000	0.60%	30180.00
7	30000	0.70%	30210.00
8	30000	0.80%	30240.00
9	30000	0.90%	30270.00
10	30000	1.00%	30300.00
11	30000	1.10%	30330.00
12	30000	1.20%	30360.00
13	30000	1.30%	30390.00
14	30000	1.40%	30420.00
15	30000	1.50%	30450.00
16	30000	0.15%	30045.00
17	30000	0.25%	30075.00
18	30000	0.35%	30105.00
19	30000	0.45%	30135.00
20	30000	0.55%	30165.00
21	30000	0.65%	30195.00
22	30000	0.75%	30225.00
23	30000	0.85%	30255.00
24	30000	0.95%	30285.00
25	30000	1.05%	30315.00
26	30000	1.15%	30345.00
27	30000	1.25%	30375.00
28	30000	1.35%	30405.00
29	30000	1.45%	30435.00
30	30000	0.12%	30036.00
31	30000	0.22%	30066.00
32	30000	0.32%	30096.00
33	30000	0.42%	30126.00
34	30000	0.52%	30156.00
35	30000	0.62%	30186.00
36	30000	0.72%	30216.00
37	30000	0.82%	30246.00
38	30000	0.92%	30276.00
39	30000	1.02%	30306.00
40	30000	1.12%	30336.00
41	30000	1.22%	30366.00
42	30000	1.32%	30396.00
43	30000	1.42%	30426.00
44	30000	0.18%	30054.00
45	30000	0.28%	30084.00
46	30000	0.38%	30114.00
47	30000	0.48%	30144.00
48	30000	0.58%	30174.00
49	30000	0.68%	30204.00
50	30000	0.78%	30234.00

Decrease in value (negative percentage change)-

Set	X (Value Before Rebase)	Y (Percentage Change)	Z (Value After Rebase)
1	30000	0.10%	29970.00
2	30000	0.20%	29940.00
3	30000	0.30%	29910.00
4	30000	0.40%	29880.00
5	30000	0.50%	29850.00
6	30000	0.60%	29820.00
7	30000	0.70%	29790.00

8	30000	0.80%	29760.00
9	30000	0.90%	29730.00
10	30000	1.00%	29700.00
11	30000	1.10%	29670.00
12	30000	1.20%	29640.00
13	30000	1.30%	29610.00
14	30000	1.40%	29580.00
15	30000	1.50%	29550.00
16	30000	0.15%	29955.00
17	30000	0.25%	29925.00
18	30000	0.35%	29895.00
19	30000	0.45%	29865.00
20	30000	0.55%	29835.00
21	30000	0.65%	29805.00
22	30000	0.75%	29775.00
23	30000	0.85%	29745.00
24	30000	0.95%	29715.00
25	30000	1.05%	29685.00
26	30000	1.15%	29655.00
27	30000	1.25%	29625.00
28	30000	1.35%	29595.00
29	30000	1.45%	29565.00
30	30000	0.12%	29964.00
31	30000	0.22%	29934.00
32	30000	0.32%	29904.00
33	30000	0.42%	29874.00
34	30000	0.52%	29844.00
35	30000	0.62%	29814.00
36	30000	0.72%	29784.00
37	30000	0.82%	29754.00
38	30000	0.92%	29724.00
39	30000	1.02%	29694.00
40	30000	1.12%	29664.00
41	30000	1.22%	29634.00
42	30000	1.32%	29604.00
43	30000	1.42%	29574.00
44	30000	0.18%	29946.00
45	30000	0.28%	29916.00
46	30000	0.38%	29886.00
47	30000	0.48%	29856.00
48	30000	0.58%	29826.00
49	30000	0.68%	29796.00
50	30000	0.78%	29766.00

- Cleaning of Data:

  A dataset must first be cleaned before being ready for machine learning. It entails locating and fixing or eliminating mistakes, discrepancies, and missing values from the dataset. Here, firstly all missing values and duplicate values were found. Missing values were removed by replacing empty blanks with Mean/Median values of the dataset. Duplicate values can skew analysis and can reduce the effectiveness of machine learning algorithms, so they were also removed. After that data is pre-processed and normalized. Standardization of data was also performed as machine learning algorithms perform better with this. Finally, the standard data set is obtained for further processing.

- Training and Testing of Data:

  The training and result output was divided in a 70:30. A sample set of 100 training output (50 for upside and 50 for downside) is shared above.
  Training and testing of data are critical steps in the development of machine learning models. Machine learning models can sometimes memorize the training data instead of learning the underlying patterns. This is known as overfitting, and it can lead to poor performance on new, unseen data. Testing the model on a separate test set helps to ensure that it is not overfitting to the training data. Testing the model on a separate test set allows us to assess its performance on new, unseen data. This provides a more accurate estimate of how well the model is likely to perform in the real world.

- Selection of ML Algorithms:

  The algorithms which were selected for performing analysis were chosen based on size and complexity of dataset, the available computational resources, and the desired performance metrics. It's important to note that there is no one-size-fits-all solution when it comes to selecting the best algorithm for a given problem. It often requires experimentation and fine-tuning to determine the best approach for a particular dataset and problem.

- Comparison and Conclusion:

  For finding if the value is going up or down, in this case, we import the historical data first before engineering a new feature called up down that is set to 1 if the value is increasing and 0 if it is decreasing. The data is then divided into training and testing sets, a logistic regression model is trained on the training data, and its performance is assessed using the accuracy score. Keep in mind that this is just one example and that, depending on the details of the data and the situation at hand, other machine learning algorithms and techniques may be employed to solve this issue. And to find the output after rebasing with the help of code, we generate a sample dataset where X stands for the current value and % change and Y for the result. The Logistic Regression class of scikit-learn was then used to fit a linear regression model. We then use some fresh data to test the model, printing the results.

IV. Results

The dataset was divided in the ratio of 70 percent training data and remaining 30 percent was testing data. There are various factors to evaluate efficiency of a classification model. The Three major useful factors are 1. Accuracy, 2. Precision, 3. Recall and 4. F1-score. Accuracy helps us in measuring the ratio of correct predictions made by the model from the total number of predictions made. But for accuracy to give good results data shouldn't be imbalanced, otherwise it can be misleading. Precision on the other hand measures the proportion of true positive over the total number of positive predictions made. Simply, Precision calculates the ability of the model to correctly predict the positive class. Recall calculates to what extent the model can discover the positive samples. F1-score is defined as harmonic mean of precision and recall. It performs good with imbalanced classes. Overall, precision, recall, f1-score are most useful when classes are imbalanced while accuracy performs well with balanced classes.

F1 score = 2 * (precision * recall) / (precision + recall)

Now let's look at all the results that were obtained by applying the desired algorithm:

Output-

- For Increment in value-

Set	X (Value Before Rebase)	Y (Percentage Change)	Z (Value After Rebase)	$H = \frac{Z}{X}$
1	30000	0.10%	30030.00	1.0010
2	30000	0.20%	30060.00	1.0020
3	30000	0.30%	30090.00	1.0030
4	30000	0.40%	30120.00	1.0040
5	30000	0.50%	30150.00	1.0050
6	30000	0.60%	30180.00	1.0060
7	30000	0.70%	30210.00	1.0070
8	30000	0.80%	30240.00	1.0080
9	30000	0.90%	30270.00	1.0090
10	30000	1.00%	30300.00	1.0100
11	30000	1.10%	30330.00	1.0110
12	30000	1.20%	30360.00	1.0120
13	30000	1.30%	30390.00	1.0130
14	30000	1.40%	30420.00	1.0140
15	30000	1.50%	30450.00	1.0150
16	30000	0.15%	30045.00	1.0015
17	30000	0.25%	30075.00	1.0025
18	30000	0.35%	30105.00	1.0035
19	30000	0.45%	30135.00	1.0045
20	30000	0.55%	30165.00	1.0055
21	30000	0.65%	30195.00	1.0065
22	30000	0.75%	30225.00	1.0075
23	30000	0.85%	30255.00	1.0085
24	30000	0.95%	30285.00	1.0095
25	30000	1.05%	30315.00	1.0105
26	30000	1.15%	30345.00	1.0115
27	30000	1.25%	30375.00	1.0125
28	30000	1.35%	30405.00	1.0135
29	30000	1.45%	30435.00	1.0145
30	30000	0.12%	30036.00	1.0012
31	30000	0.22%	30066.00	1.0022
32	30000	0.32%	30096.00	1.0032
33	30000	0.42%	30126.00	1.0042
34	30000	0.52%	30156.00	1.0052
35	30000	0.62%	30186.00	1.0062
36	30000	0.72%	30216.00	1.0072
37	30000	0.82%	30246.00	1.0082
38	30000	0.92%	30276.00	1.0092
39	30000	1.02%	30306.00	1.0102
40	30000	1.12%	30336.00	1.0112

41	30000	1.22%	30366.00	1.0122
42	30000	1.32%	30396.00	1.0132
43	30000	1.42%	30426.00	1.0142
44	30000	0.18%	30054.00	1.0018
45	30000	0.28%	30084.00	1.0028
46	30000	0.38%	30114.00	1.0038
47	30000	0.48%	30144.00	1.0048
48	30000	0.58%	30174.00	1.0058
49	30000	0.68%	30204.00	1.0068
50	30000	0.78%	30234.00	1.0078

- *For Decrement in value-*

Set	X (Value Before Rebase)	Y (Percentage Change)	Z (Value After Rebase)	$H = \frac{Z}{X}$
1	30000	0.10%	29970.00	0.9990
2	30000	0.20%	29940.00	0.9980
3	30000	0.30%	29910.00	0.9970
4	30000	0.40%	29880.00	0.9960
5	30000	0.50%	29850.00	0.9950
6	30000	0.60%	29820.00	0.9940
7	30000	0.70%	29790.00	0.9930
8	30000	0.80%	29760.00	0.9920
9	30000	0.90%	29730.00	0.9910
10	30000	1.00%	29700.00	0.9900
11	30000	1.10%	29670.00	0.9890
12	30000	1.20%	29640.00	0.9880
13	30000	1.30%	29610.00	0.9870
14	30000	1.40%	29580.00	0.9860
15	30000	1.50%	29550.00	0.9850
16	30000	0.15%	29955.00	0.9985
17	30000	0.25%	29925.00	0.9975
18	30000	0.35%	29895.00	0.9965
19	30000	0.45%	29865.00	0.9955
20	30000	0.55%	29835.00	0.9945
21	30000	0.65%	29805.00	0.9935
22	30000	0.75%	29775.00	0.9925
23	30000	0.85%	29745.00	0.9915
24	30000	0.95%	29715.00	0.9905
25	30000	1.05%	29685.00	0.9895
26	30000	1.15%	29655.00	0.9885
27	30000	1.25%	29625.00	0.9875
28	30000	1.35%	29595.00	0.9865
29	30000	1.45%	29565.00	0.9855
30	30000	0.12%	29964.00	0.9988
31	30000	0.22%	29934.00	0.9978
32	30000	0.32%	29904.00	0.9968
33	30000	0.42%	29874.00	0.9958
34	30000	0.52%	29844.00	0.9948
35	30000	0.62%	29814.00	0.9938
36	30000	0.72%	29784.00	0.9928
37	30000	0.82%	29754.00	0.9918
38	30000	0.92%	29724.00	0.9908
39	30000	1.02%	29694.00	0.9898
40	30000	1.12%	29664.00	0.9888
41	30000	1.22%	29634.00	0.9878
42	30000	1.32%	29604.00	0.9868
43	30000	1.42%	29574.00	0.9858
44	30000	0.18%	29946.00	0.9982
45	30000	0.28%	29916.00	0.9972
46	30000	0.38%	29886.00	0.9962
47	30000	0.48%	29856.00	0.9952
48	30000	0.58%	29826.00	0.9942
49	30000	0.68%	29796.00	0.9932
50	30000	0.78%	29766.00	0.9922

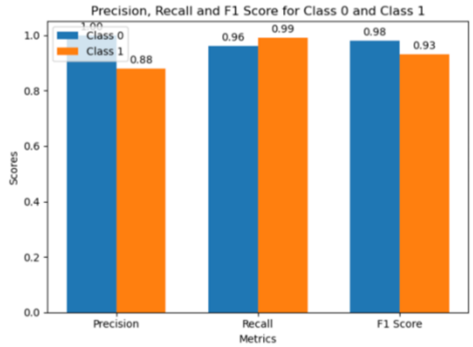
- *Classification using LSTM*

Precision, recall, F1-score, and support label obtained using Logistic Regression are mentioned in TABLE I. Overall accuracy for LSTM was 97%.

Table I

	precision	recall	f1-score
0	1.00	0.96	0.98
1	0.88	0.99	0.93

Bar graph showing precision, recall and F1 score



- *Advantages*

  This crypto is a mix of collateralized and algorithmic techniques, minimise the disadvantages of both, for instance collateralized prevent the death spiral which is caused among algorithmic run crypto causing mechanism collapse, when there is no consistent demand for the crypto and collateralizing it against a metric allow to give it, its initial value and have strong fundamental and building trust among the user/holders of the crypto.

- Comparison to other Rebase Crypto Currency-
  1. Ampleforth (AMPL) - is the origin of the rebasing mechanism. It is an ERC 20 token and pegged to a price of a Dollar and rebases after every 24 hours.

Value graph of AMPL

For reference the above is a 7-day graph of AMPL and despite rebasing after every 24 hours, it has gone through a fluctuation of 10.5%.

2. Olympus (OHM) - Rebases after every 8 hours (also experience high volatility as seen in the graph below, a spike on 21st may from 12.18 to 13 that is a change of 6.7%).

Value graph of OHM

3. Digg (DIGG) - Rebase after every 24 hours, target price is set between 1.05 and 0.95 BTC. If the price remains in this range, no rebasing will occur

In our Crypto, rebasing will occur after every 50 mins (Having 50 is not a strict rule but 50 is choose as Pomodoro Technique), to continuously keep the value stable and there is a threshold range of $\pm$1.5%. If the value goes beyond the range of $\pm$1.5%. Trading will automatically stop, and rebasing will occur. Use of LSTM algorithms will allow to retain information from previous data points and use it to forecast future values, making them suitable for handling the sequential nature of time series data.

V. Conclusion

In this research, we explored the potential of using the rebasing technique to stabilize the price of cryptocurrencies. By periodically adjusting the total supply of a cryptocurrency based on a selected benchmark, we aimed to mitigate the inherent volatility that has hindered the widespread adoption of cryptocurrencies as a medium of exchange. Our study demonstrated that rebasing can effectively control a cryptocurrency's price while preserving the integrity of its decentralized architecture. The proposed research work has used 1000 input test database classifiers. Each database produced almost similar accuracies. All accuracies were compared for LSTM, logistic regression & linear regression and LSTM performed best with excellent accuracy of 99.97%. So, with observations based on accuracies these LSTM came out to be best classifiers for finding accuracies for the given dataset and can be used for future classifications. The model is helpful for supporting stability of cryptocurrency on several attributes. In conclusion, while rebasing shows promise as a tool for stabilizing cryptocurrency prices, it is essential to consider the associated risks and challenges. Future research should focus on refining rebasing mechanisms, exploring hybrid approaches that combine collateralized and algorithmic techniques, and developing robust governance frameworks to ensure the stability and integrity of cryptocurrencies. By addressing these areas, we can pave the way for a more stable and reliable cryptocurrency ecosystem.

References

[1] Antonio Briola, David Vidal-Tomás, Yuanrong Wang, Tomaso Aste "Anatomy of a Stablecoin's failure: The Terra-Luna case" Journal of International Money and Finance Volume 51, January 2023, Article number 103358.

[2] Gregory Gadzinski, Alessio Castello, Florie Mazzorana "Stablecoins: Does design affect stability?" Journal of International Money and Finance Volume 53, May 2023, Article number 103611.

[3] Paul P. Momtaz "The Pricing and Performance of Cryptocurrency".

[4] Hanna Kołodziejczyk, Klaudia Jarno "Stablecoin – the stable cryptocurrency".

[5] Nader Al-Naji, Josh Chen, Lawrence Diao "Basis: A Price-Stable Cryptocurrency with an Algorithmic Central Bank".

[6] Richard K. Lyons, Ganesh Viswanath-Natraj "What keeps stablecoins stable?" Journal of International Money and Finance Volume 131, March 2023, Article number 102777.

[7] W. Yiying and Z. Yeze, "Cryptocurrency Price Analysis with Artificial Intelligence," 2019 5th International Conference on Information Management (ICIM), Cambridge, UK, 2019, pp. 97-101.

[8] F. Sabry, W. Labda, A. Erbad and Q. Malluhi, "Cryptocurrencies and Artificial Intelligence: Challenges and Opportunities," in IEEE Access, vol. 8, pp. 175840-175858, 2020.

[9] Alessandretti, L., ElBahrawy, A., Aiello, L. M. & Baronchelli, A. (2018). Machine Learning the Cryptocurrency Market. Complexity, 2018.

Author 1 - Homedeep Singh Saggu

Homedeep Singh Saggu is a final year engineering student at Manipal University Jaipur, pursuing a degree in Computer and Communication Engineering. With a keen interest in the rapidly evolving fields of cybersecurity and blockchain technology. His coursework has provided him with a solid foundation in computer and communication engineering, while his specialization in cybersecurity and blockchain has allowed him to delve deeper into these cutting-edge domains. He aims to contribute to the development of robust and resilient systems that can withstand the ever-evolving threats in the digital landscape. He is an active member of the university's cybersecurity club, where he collaborates with like-minded individuals in the field. He has also participated in several hackathons and coding competitions, showcasing his technical prowess and ability to work effectively in a team environment.

Author 2 - Manoj R

Manoj R, an academician with B.E., MTech and currently pursuing his PhD in CSE in block chain technology. He is working as an assistant professor at the Department of Computer Science & Engineering at Manipal Institute of Technology, Manipal Academy of Higher Education (MAHE), Manipal, Karnataka, India. He has an academic experience of more than 15 years. He has presented and published more than 20 papers in reputed journals and conferences of international repute. He has reviewed many research papers for reputed journals and conferences. His research interests cover cryptography and network security, and block chain and its applications.

Author 3 - Anmol Singh Gill
Anmol Singh Gill is a third-year student at Manipal University Jaipur, specializing in Computer Science Engineering. He has developed a profound interest in artificial intelligence and machine learning (AI/ML), driven by their vast potential to revolutionize industries and enhance human capabilities. He is fascinated by the advancements in autonomous systems, including self-driving cars, drones, and robotics. He believes that AI/ML can significantly improve the safety, reliability, and efficiency of these systems, paving the way for smarter cities and more sustainable modes of transportation. His enthusiasm for AI/ML is fueled by the transformative impact these technologies can have on data-driven decision-making, automation, and predictive analytics. He is particularly excited about the applications of AI/ML in healthcare, finance, and autonomous systems. He aspires to innovate and contribute to the creation of intelligent systems that can solve complex real-world problems.