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Dynamic Constant Product Market Maker Using Cryptocurrency Price Prediction Based on Deep Learning

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딥러닝 기반의 암호화폐 가격 예측을 사용한 동적 상수 곱 마켓 메이커

Dynamic Constant Product Market Maker Using Cryptocurrency Price Prediction Based on Deep Learning

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Abstract

These days the Decentralized Finance(DeFi) market has grown. In particular, the Decentralized Exchange(DEX) is the most popular and large DeFi application. A great number of DEX use Automated Market Maker(AMM) which is a mathematical algorithm to decide the price of the assets. However, AMM has drawbacks called slippage and impermanent loss. In this paper, we briefly review the related concepts and dynamic curves introduced by Bhaskar et al. We suggest a dynamic constant product market maker using cryptocurrency price prediction based on deep learning. Using cryptocurrency price prediction based on deep learning, our system aims to give lower latency and higher accurate price than using decentralized oracle data feed. Changing the curve following the predicted price, the system can mitigate impermanent loss and give more profit to liquidity providers.

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I. Introduction

1.1 Background

Blockchain is a decentralized network that stores and manages data without a centralized custodian. Smart contract is a program that automatically executes a transaction that was written in advance when requirements are met. There is no central server or organization in the blockchain, so users have to maintain the network. Users who contribute to the blockchain networks can get cryptocurrencies as a reward. Recently, cryptocurrencies including BTC in Bitcoin and ETH in Ethereum are regarded as having economical values. Plenty of people take an interest and invested in cryptocurrencies. In April 2022, the market volume of BTC has reached $744 billion and the market volume of ETH has reached $ 345 billion.

As expanding the cryptocurrency market, Decentralized Finance (DeFi) market also is growing. DeFi is a new financial ecosystem without a centralized custodian. There are various DeFi services such as decentralized loans, bonds, derivatives, insurance, exchanges, lottery, prediction market, and fund management.

Among them, Decentralized Exchange (DEX) is the most popular application. DEX is a new cryptocurrency exchange operated on the blockchain. Cryptocurrencies are different for each blockchain network. Conventionally, those who want to exchange cryptocurrencies have used centralized exchanges such as Coinbase, and Binance. However, using centralized exchanges has drawbacks. The first one is complexity. Using centralized exchange has a complex process. Most of them require identity verification. The second one is security. Centralized exchange can be exposed to cyber-attacks. For instance, in 2021, Coinbase suffered from a cyber-phishing attack, and 6000 users were stolen their cryptocurrencies. The third one is transparency. No one cannot know their inside operations and trust them entirely. The last one is privacy. There might be censorship and make regulations. DEX can be an alternative that solves those drawbacks.

DEX uses a smart contract and Automated Market Maker (AMM). AMM is an algorithm that calculates the cryptocurrency price according to a mathematical formula. It was introduced to a prediction market at first. There were several algorithms including Logarithmic Market Scoring Rule (LMSR) [1] and Liquidity Sensitive LMSR (LS-LMSR) [2]. However, these algorithms are not a good model for DEX [3]. Meanwhile Vitalik buterin suggested Constant Product Market Maker (CPMM) for decentralized exchange [4].

CPMM follows $x \cdot y = k$ equation. x and y are reserves of each asset. k is constant that made by product of x and y. Slippage and impermanent loss are two downsides of CPMM. Slippage occurs when the expected price of assets differs from the actual price of assets. Impermanent loss, also known as divergence loss occurs when a liquidity provider withdraws their assets due to difference in value between when liquidity was provided to the pool and when the assets are simply held. As a compensation for the impermanent loss, liquidity providers receive transaction fees.

However, according to a study conducted by Bancor [5], 49.5% of Uniswap, which uses CPMM, liquidity providers yielded negative returns due to the impermanent loss. Impermanent loss exceeds trading fee profit. It is more advantageous to simply hold assets rather than provide liquidity.

1.2 Related works

Several attempts have been made to solve the slippage and impermanent loss problem.

Bancor uses impermanent loss insurance [6]. Impermanent loss is covered by insurance. Liquidity providers get governance tokens as a result of their impermanent loss.

Dynamic swap fees are used by KyberSwap [7] and Bancor. Swap fees increases when the market is stable and decreases when the market is highly volatile. Dynamic swap fees reduce the impact of divergence loss for the liquidity providers.

Uniswap v3 introduced concentrated liquidity [8]. At the point of adding liquidity, liquidity providers determine the price range. Provided liquidity is only activated within that range. It solves the slippage problem.

Curve Finance uses stable swap algorithm [9]. Stable swap combines constant sum and constant product to minimize slippage. When a trading size is small and market is balanced, constant sum is applied. When a trading size is big and market is imbalanced, constant product is applied.

Wang suggested the constant circle and ellipse curve based automated market maker [3]. It has a fixed price amplitude. So, the range of slippage and impermanent loss is fixed. Plus, the slope function of a tangent line changes smoothly. The token price fluctuation is quite smooth. As a result, it has a relatively low slippage.

Bhaskar et all. proposed the concept of dynamic curve-based AMM decentralized exchanges [10]. The curve is continuously and automatically adjusted to a current pool price equal to a market price. There are no arbitrage opportunities and impermanent loss.

1.3 Problem

As we have mentioned before, impermanent loss and slippage are problems for the constant product market maker. Trader and liquidity provider may lose their assets because of impermanent loss and slippage. It disturbs users' participation and activation of the DEX. We aim to solve impermanent loss and slippage issue.

We get an idea from Bahskar's dynamic curve-based AMM DEX. This mechanism requires an external market price information with low-latency and accuracy. Oracle data feed services transfers external market cryptocurrency price data into the blockchain network. To the best of our knowledge, there is currently no complete real-time decentralized oracle data feed.

We propose dynamic constant product market maker using cryptocurrency price prediction based on deep learning. Instead of using the data feed, this system uses deep learning to forecast cryptocurrency prices and adjusts the curve based on the predicted result. Using predicted price results aims to give lower latency and higher accurate price than using decentralized oracle data feed. The system allows for mitigating impermanent loss.

The following are the main contributions of this paper.

- We proposed a dynamic constant product AMM using cryptocurrency price prediction based on deep learning.
- To evaluate the performance of the system, simulation experiments have been conducted.

The remainder of this paper is organized as follows: Section 2 covered key concepts with the dynamic curves and price prediction. Section 3 introduces the detailed designs of the proposed system. Section 4 presents experiments as well as results. Section 5 concludes the paper and discusses future works.

II. Preliminaries

2.1 Constant Product Market Maker (CPMM)

CPMM is the most popular AMM. Vitalik buterin suggested the constant product market maker for decentralized exchange [4]. CPMM follows $x \cdot y = k$ equation. x denotes the quantity of X token. y denotes the quantity of Y token. k is constant that made by product of x and y. Reserve of x is $\sqrt{\frac{k}{MarketPrice}}$. Reserve of y is $\sqrt{k \cdot MarketPrice}$. The price of assets is automatically determined according to a ratio of assets balance while maintaining the k value. When the liquidity is added or reduced and when trading fee is collected, k can be changed. At the beginning of supplying liquidity, pool smart contract is created and assets are stored to the contract. Using this pool, user exchanges their assets. CPMM was implement by Uniswap team and Uniswap is most popular DEX project. There are two downsides of the constant product market maker called slippage and impermanent loss.

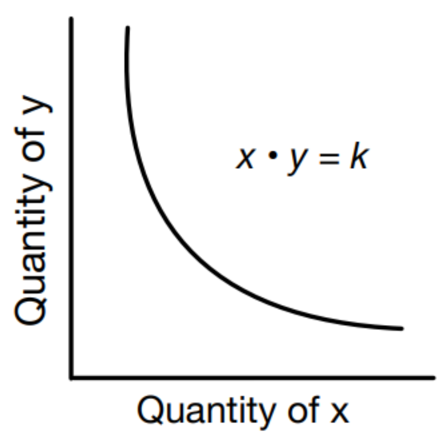

FIGURE 1. CPMM price curve

2.2 Slippage

Slippage is derivations between an expected return value of asset and an actual return value of asset. Slippage is caused by a change in state as a result of latency between transaction execution and completion, as well as a lack of liquidity. Slippage results in loss of profit for the trader and front-runner attack. For example, Alice wants to exchange X tokens to Y tokens. Let price ratio of X token and Y token is 1: 2 when executing transaction. Then Alice expects that she will get 4 Y tokens for 2 X tokens. However, If the price ratio changes to 1:1 when completing transaction, Alice will actually get 2 Y tokens. Here the derivation 2Y tokens are slippage. If the price ratio changes to 1: 4, Alice will actually get 8 Y tokens. Here the derivation 4Y tokens also are slippage.

2.3 Impermanent loss (Divergence loss)

Impermanent loss or divergence loss is difference caused by change in value between when liquidity was provided to the pool and when the assets are simply held. External change in the market value of assets and the change of pool price cause the difference. As a compensation for the impermanent loss, liquidity providers receive transaction fees. For instance, let market price ratio of X token and Y token is 1:100. Alice supply 100 X tokens and 10,000 Y tokens to the pool. Alice has a $100 \cdot 100 + 10{,}000 = 20{,}000$ as Y token value. The price ratio has changed to 1:110. Bob swaps 488 Y tokens to 4.652 X tokens to get an arbitrage opportunity. After swaps, the reserves of the pool are 95.348 X tokens and 10488 Y tokens. Then the pool price ratio will be changed to 1: 110. Now Alice has $95.348 \cdot 110 + 10488 = 20976.28$ as Y token value. But If Alice just held the tokens, then Alice might have $100 \cdot 110 + 10000 = 21000$ as Y token value. The difference 23.72 is loss for Alice. It is called impermanent loss.

2.4 Dynamic curve based automated market maker

Dynamic curve-based AMM was suggested [10]. The price curve is continuously and automatically adjusted the current pool price equals the market price. It utilizes market price input to modify the mathematical relationship between the assets. The pool price does not change if the market price does not change. Thus there are no arbitrage opportunities and impermanent loss. This mechanism requires an external oracle that provides low-latency and accurate market prices.

Dynamic constant product curve is as follows:

$$w(t) \cdot \big(x(t) - a(t)\big) \cdot y(t) = k \qquad (1)$$

$x(t)$ and $y(t)$ are reserves of each token at t time. $x(t)$ and $y(t)$ is positive. $a(t)$ is less than $x(t)$. $w(t)$ is positive. The price of the dynamic constant product curve is as follows:

$$\mathrm{p_X(t)} = \frac{\mathrm{k}}{\mathrm{w(t)}} \cdot \frac{1}{\big(\mathrm{x(t)} - \mathrm{a(t)}\big)^2} \qquad (2)$$

When the market price changes, $\mathrm{w(t)}$ and $\mathrm{a(t)}$ change in order to ensure that the new market price $\mathrm{p_{mkt}(t)} = \mathrm{p_X(t)}$ and the new curve intersects the current liquidity pair of $(\mathrm{x(t)}, \mathrm{y(t)})$. Solving systems of two equation (1) and (2), we can get two unknowns $\mathrm{a(t)}$ and $\mathrm{w(t)}$ as follows:

$$a(t) = x(t) - \frac{y(t)}{p_{mkt}(t)}$$

$$w(t) = \frac{k \cdot p_{mkt}(t)}{y(t)^2}$$

$a(t)$ is less than $\mathrm{x(t)}$ and $\mathrm{w(t)}$ is positive, when k, $\mathrm{p_{mkt}(t)}$, $\mathrm{x(t)}$ and $\mathrm{y(t)}$ are all positive.

In the dynamic curve-based AMM, traders get an output amount which is a return values against input amount:

$$Output\ amount = y - \frac{k}{w(t)(x(t) + \Delta x - a(t))}$$

Derivation is as follows:

Let $x(t)$ and $y(t)$ are token supplies, Δx and Δy are input amount and output amount respectively.

By the definition of the DCPMM, k value has to be constant after trading. Thus,

$$w(t)\big(x(t) - a(t)\big) \cdot y(t) = w(t)(x(t) + \ \Delta x - a(t))(y(t) - \Delta y) = k$$

must hold. Then,

$$w(t)(x(t) + \ \Delta x - a(t))(y(t) - \Delta y) = k$$

$$\frac{k}{w(t)(x(t) + \Delta x - a(t))} = y(t) - \Delta y.$$

Finally output amount is,

$$\Delta \mathrm{y} = \mathrm{y(t)} - \frac{k}{w(t)\big(x(t) + \Delta x - a(t)\big)}.$$

We will derive reserves of x and y.

Remind (1) and (2),

$$\begin{cases} w(t)\big(x(t) - a(t)\big) \cdot y(t) = k & (1) \\ \dfrac{k}{w(t)} \cdot \dfrac{1}{\big(x - a(t)\big)^2} = p_{mkt}(t) & (2) \end{cases}$$

From the equation (2),

$$\frac{1}{(x(t) - a(t))^2} = \frac{p_{mkt}(t) \cdot w(t)}{k}$$

$$(x(t) - a(t))^2 = \frac{k}{p_{mkt}(t) \cdot w(t)}$$

$$(\mathrm{x(t)} - \mathrm{a(t)}) = \sqrt{\frac{k}{p_{mkt}(t) \cdot w(t)}}. \quad (3)$$

Finally reserve of the x is,

$$\mathrm{x(t)} = \sqrt{\frac{k}{p_{mkt}(t) \cdot w(t)}} + a(\mathrm{t})\,.$$

Next, from the equation (1),

$$(\mathrm{x(t)} - \mathrm{a(t)}) = \frac{k}{w(t) \cdot y(t)}$$

Substituting the equation (3),

$$\sqrt{\frac{k}{p_{mkt}(t)}} = \frac{k}{w(t) \cdot y(t)}\,.$$

Finally, the reserve of y becomes

$$\mathrm{y(t)} = \frac{k}{w(t)} \cdot \frac{1}{\sqrt{\frac{k}{p_{mkt}(t)}}}\,.$$

2.5 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a deep learning model with cycle structure makes previous event affect the future event [11]. The model can handle long-term dependencies as well as short-term memory. It is frequently used for time series data such as price and natural language. The LSTM is composed of a cell state, a hidden state, forget gate, input gate, and output gate. Cell state memorizes long-term state. and hidden state memorized short-term state. Three gates distinguish importance and update information.

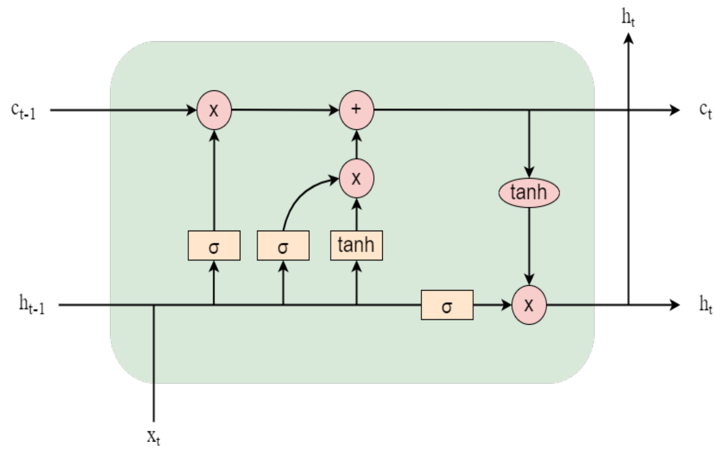

FIGURE 2 Long Short-Term Memory

III. Dynamic Constant Product Market Maker Using Cryptocurrency Prediction Based on Deep Learning

We propose a dynamic constant product AMM using cryptocurrency price prediction based on deep learning. This system uses deep learning to forecast cryptocurrency prices and adjusts the curve based on the predicted result.

Impermanent loss and slippage are problems for the constant product market maker. Trader and liquidity provider may lose their assets because of the problems. It disturbs users' participation and activation of the DEX. We aim to solve impermanent loss and slippage issue. We get an idea from Bhaskar's dynamic curve-based AMM DEX. This mechanism requires an external market price information with low-latency and accuracy. Oracle is system that allows real-world off-chain data to be imported into the blockchain. There are decentralized oracle services such as Chainlink, Band protocol and Witnet. These oracles have data feed service. Data feed provides standard data such as cryptocurrency price on its own. However, data feed can't give complete real-time data. Thus, we don't use data feed service. Instead, we simply use decentralized oracle to directly transfer predicted price data. Using predicted price results seeks to give lower latency and higher accurate price than using data feed. As a result, the system allows for mitigating impermanent loss.

The system consists of three parts: Price prediction API, Decentralized oracle, and Dynamic constant product market maker DEX. The deep learning part makes use of historical cryptocurrency price data. We used Long Short-Term Memory (LSTM) to predict cryptocurrency price. We made the price prediction model into an API. Decentralized oracle requests the price prediction results to the API. The API responses to the oracle. DCPMM DEX deployed on the Ethereum network requests external information to the oracle. Oracle responses to the DEX's request. The DCPMM DEX adjusts the curve refers to predicted price results.

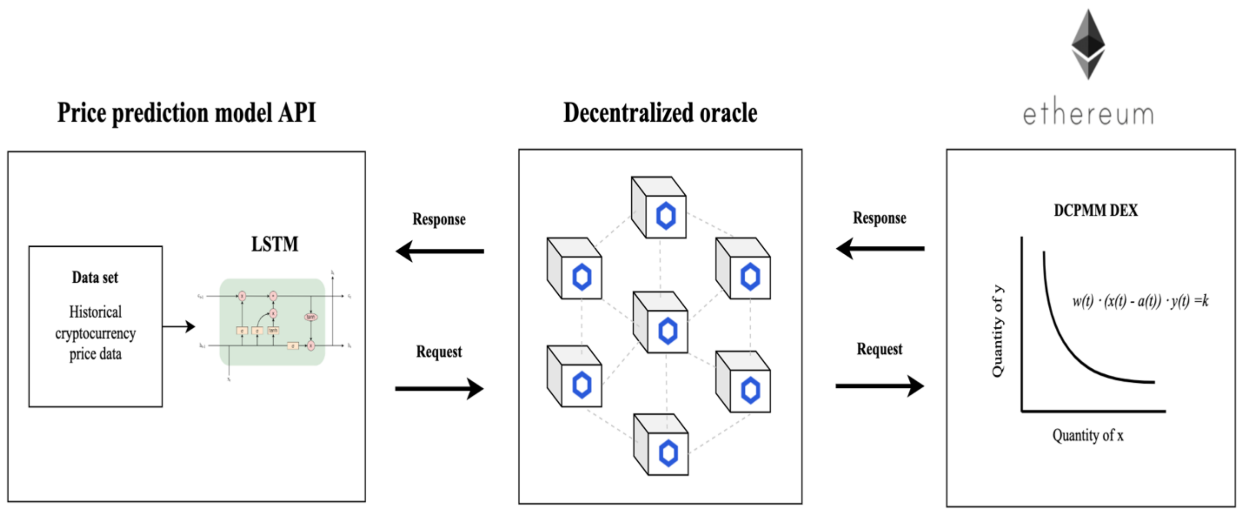

FIGURE 3 Overall structure

IV. Experiments and Result

5.1 Set up

We conducted simulations to evaluate the performance of the system. Simulations conducted on three scenarios: when the curve is fixed (CPMM), when the curve changed (DCPMM) according to the actual market price and when the curve changed (DCPMM) according to the predicted price.

We get BTC/ETH historical price data from Yahoo Finance. Data was collected from 1st, January 2020 to 31st, December 2021 period. Total data size is 691 rows.

1	Date	Open	High	Low	Close	Adj Close	Volume
2	2020.1.1	55.51149	54.825542	55.494766	55.04636	55.04636	141937156
3	2020.1.2	55.064529	55.247189	54.442657	54.826622	54.826622	163268611
4	2020.1.3	54.818447	55.35413	54.654873	54.74242	54.74242	209518687
5	2020.1.4	54.746078	54.616806	54.712635	54.865559	54.865559	136554062
6	2020.1.5	54.86404	54.233013	54.512573	54.3843	54.3843	144742740

FIGURE 4 Cryptocurrency price dataset

We used a deep learning model and close price data for predicting cryptocurrency price. The data is split into 491 training sets and 200 test sets. Min-max normalization is used to scale the data in the range [0,1]. The model has 2 LSTM layers and 1 Dense layer. We set the window size as 40 which means the model predicts one day using 40 days of previous data. We set batch size as 10, and epochs as 20. Adam optimizer is used. Mean squared error is used for loss function. In order to assess the model's performance, we measured the mean squared error, which is 0.0002054, and the mean absolute error, which is 0.0108949. We use Keras deep learning framework to implement price prediction model.

```
model = Sequential()
model.add(LSTM(40, return_sequences = True, input_shape = (40,1)))
model.add(LSTM(64, return_sequences = False))
model.add(Dense(1, activation='linear'))
model.compile(loss='mse', optimizer = 'adam', metrics=['mae'])
```

FIGURE 5 Cryptocurrency price prediction model

We executed a total of 20 time trades on the BTC/ETH pool. Trades consists of 10-times normal trades and 10 times arbitrage trades. Price data is from 15th, June, 2020 to 5th, July, 2022. Initial market price of BTC is 15.866826 ETH. Initial pool state is 10 BTC and 15.866826 ETH. Input amount consists of normal traders' values and arbitragers' values. Normal traders' inputs are random values following a standard normal distribution. Arbitragers' inputs are to bridge the gap between pool price and external market price. Arbitragers seek to get a profit from the difference. When the gap occurs, one-time arbitrage trade is set to close the gap. Arbitrage input is set to the difference reserves between after trading and current. Simulation starts with normal trades. Right after the normal trade, arbitrage trade follows and make pool price same as market price.

Market price does not change during the arbitrage trade. Market price is renewed when occurring normal trade but not on first trade. In the contrast, predicted price does not change during the normal trade. Predicted price is renewed after occurring arbitrage trade. In the case of DCPMM(Actual) adjusts a and w following the market price change. In the case of DCPMM(Predicted) adjusts a and w following the predicted price change.

We use impermanent loss and trading fee as metrics for the quantitative evaluation of the results. Trading fee is 0.3% of input amount. Impermanent loss is the difference between when simply hold the assets and when provide the liquidity to the pool. That is to say, $\left((10 \cdot \text{Currnet market price}) + 15.866826\right) - (\text{ reserveX } \cdot \text{Current market price} + \text{reserveY})$.

Table 1 Simulation indexes

Index	Formula
Trading fee	$Input\ amount\ \cdot 0.003$
Impermanent loss	*Value of the assets when holding – Value of the assets when providing liquidity*
Reserve X of CPMM	$\sqrt{\frac{k}{Price}}$
Output amount of CPMM	$y(t)\cdot(\frac{(Input\ amount\cdot 0.997)}{x(t)+(Input\ amount\cdot 0.997)-a(t)})$
Reserve X of DCPMM	$\sqrt{\frac{k}{Price\cdot w(t)}}+a(t)$
Output amount of DCPMM	$y-\frac{k}{w(t)(x(t)+\Delta x-a(t))}$

5.2 Results

Based on the simulations, the changing curve that tracks market price is superior than the fixed price curve, while the changing curve that tracks predicted price, that is the performance of the proposed system, is inferior. Simulation results are as follows.

5.2.1 Market price and Predicted price

Figure 6 shows the market and predicted. Market price is actual historical cryptocurrency price from Yahoo Finance. Predicted price is predicted cryptocurrency price from our deep learning model. X axis is set to time and the unit interval is 1 day. Y axis is set to prices of BTC in units ETH. Initial market price is 15.866826. Maximum value is 17.431831. Minimum value is 15.866826. Maximum value is 16.423765. Minimum value is 14.481604. Predicted price has a gap from market price. We will discuss further in the end of this chapter.

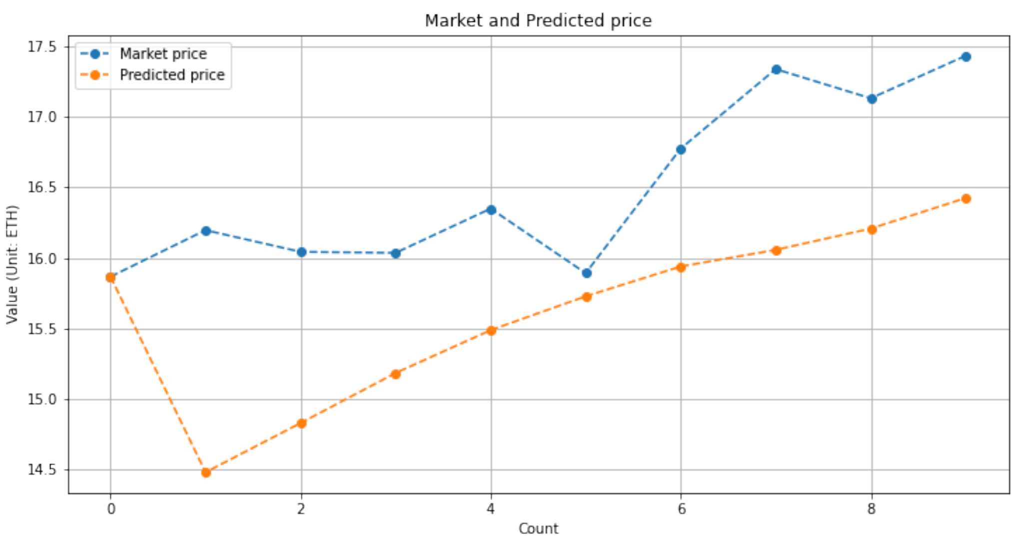

FIGURE 6 Market and Predicted price change

5.2.2 Constant Product Market Maker

Figure 7 shows the trading fee and impermanent loss of the CPMM. X axis is set to the trading counts following the trade scenario. Y axis is set to prices of BTC in units ETH. Table 2 shows the observed values of the CPMM trading fee and impermanent loss. Trading fee is similar with previous results. Maximum value of the trading fee is 0.11383547724799559. Minimum value of the trading fee is 0.003326511860771042. Maximum value of the impermanent loss is 0.37563182600450773. Minimum value of the impermanent loss is 0.00009652595986153756. Impermanent loss is increased highly after 11 count as the market price fluctuated in the second half.

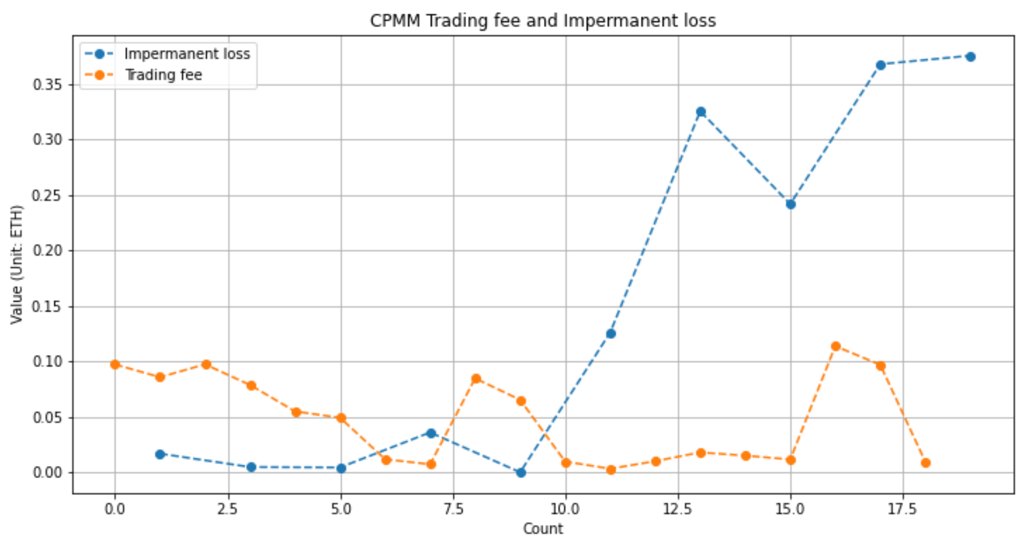

FIGURE 7 CPMM Trading fee and Impermanent loss

Table 2 CPMM the Observed Trading fee and Impermanent loss

Counts	Trading fee	Impermanent loss
1	0.09733741687146903	
2	0.08582412836470255	0.016914463956311465
3	0.09741015893361925	
4	0.07879543798394906	0.00485120533448935
5	0.05501242659790705	
6	0.049264877048027955	0.0044658974366029724
7	0.011866705958427204	
8	0.007309096313862847	0.03605725499170376
9	0.08480564626563737	
10	0.06538317824687923	0.00009652595986153756
11	0.009758974861074243	
12	0.003326511860771042	0.12606965743225373
13	0.010094019144633622	
14	0.018059749002342862	0.325555746288728
15	0.015127034488521035	
16	0.01169872725507659	0.2418985421453499
17	0.11383547724799559	
18	0.09699134984506941	0.36797195202785815
19	0.009623070125823308	
20	0.009560377988093772	0.37563182600450773

5.2.3 Dynamic Constant Product Market Maker (Actual price)

Figure 8 shows the trading fee and impermanent loss of the DCPMM (Actual price). X axis and Y axis are same as the previous. Table 3 shows the observed values of the DCPMM (Actual price) trading fee and impermanent loss. Trading fee is similar with previous results. Maximum value of trading fee is 0.11349115533181475. Minimum value of the trading fee is 0.009759130328478083. We can see the impermanent loss is always 0.

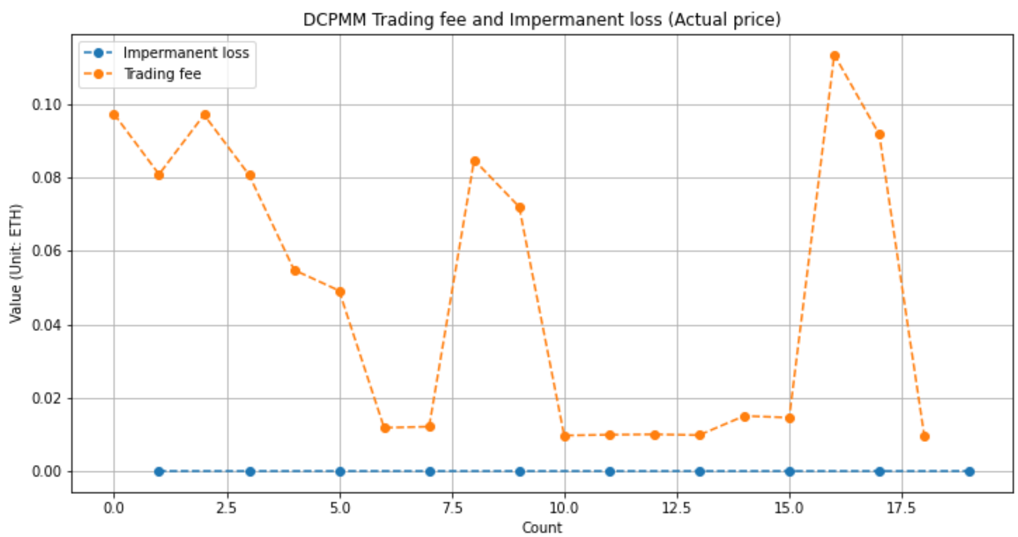

FIGURE 8 DCPMM Trading fee and Impermanent loss (Actual price)

Table 3 DCPMM (Actual) the Observed Trading fee and Impermanent loss

Counts	Trading fee	Impermanent loss
1	0.09733741687148267	
2	0.08089465666101248	0.0
3	0.09711749801977021	
4	0.0807427040095518	0.0
5	0.05484734179594852	
6	0.04921105212722665	0.0
7	0.011868262686676179	
8	0.012162377492302312	0.0
9	0.08480497311947488	
10	0.0720462360409293	0.0
11	0.009759130328478083	
12	0.009958000933522726	0.0
13	0.010063721456134544	
14	0.009856583314492795	0.0
15	0.015081595391251312	
16	0.01462112352383915	0.0
17	0.11349115533181475	
18	0.09174754972267607	0.0
19	0.009631989808262187	
20	0.009825712607607784	0.0

5.2.4 Dynamic Constant Product Market Maker (Predicted price)

Figure 9 shows the trading fee and impermanent loss of the DCPMM (Predicted price). X axis and Y axis are same as the previous. Table 4 shows the observed values of the DCPMM (Predicted price) trading fee and impermanent loss. Trading fee is similar with previous results. Maximum value of the trading fee is 0.11349115533181475. Minimum value of the trading fee is 0.009759130328478083. Impermanent loss is more than the trading fee. Maximum value of the impermanent loss is 4.905385002697017. Minimum value of the impermanent loss is 0.6369921401828265.

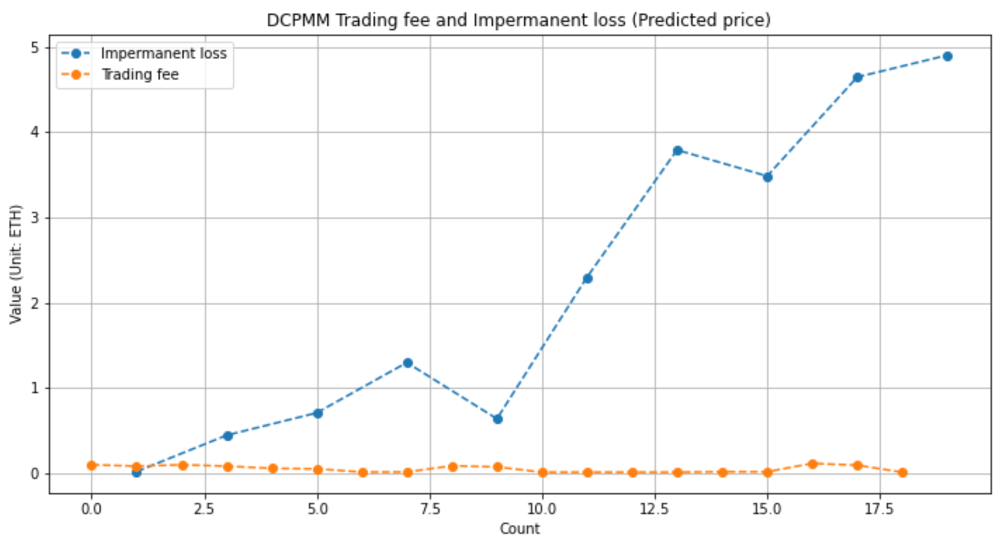

FIGURE 9 DCPMM Trading fee and Impermanent loss (Predicted price)

Table 4 DCPMM (Predicted) the Observed Trading fee and Impermanent loss

Counts	Trading fee	Impermanent loss
1	0.09733741687148267	
2	0.08089465666101248	0.016914237140554178
3	0.09711749801977021	
4	0.08074270400955186	0.44346689491476354
5	0.05484734179594852	
6	0.04921105212722665	0.7067869767844286
7	0.011868262686676179	
8	0.012162377492302312	1.2967236948127265
9	0.08480497311947488	
10	0.0720462360409293	0.6369921401828265
11	0.009759130328478083	
12	0.009958000933522726	2.2989667667458207
13	0.010063721456134544	
14	0.009856583314492795	3.793245946356251
15	0.015081595391251312	
16	0.014621123523839152	3.486339631538897
17	0.11349115533181475	
18	0.09174754972267607	4.648673714782376
19	0.009631989808262187	
20	0.009825712607607784	4.905385002697017

5.2.5 Integration

Figure 10 shows the impermanent loss of the CPMM, DCPMM (Actual), and DCPMM (Predicted) together. X axis and Y axis are same as the previous. Impermanent loss is lowest when adjusting the curve following the actual market price. Next small is fixed curve. Adjusting the curve following the predicted market price has highest impermanent loss value. Impermanent loss of DCPMM (predicted price) has a gap from market price. The cause of the gap is considered as lack of prediction accuracy. We will discuss on the accuracy issue of the price prediction further in the end of this chapter.

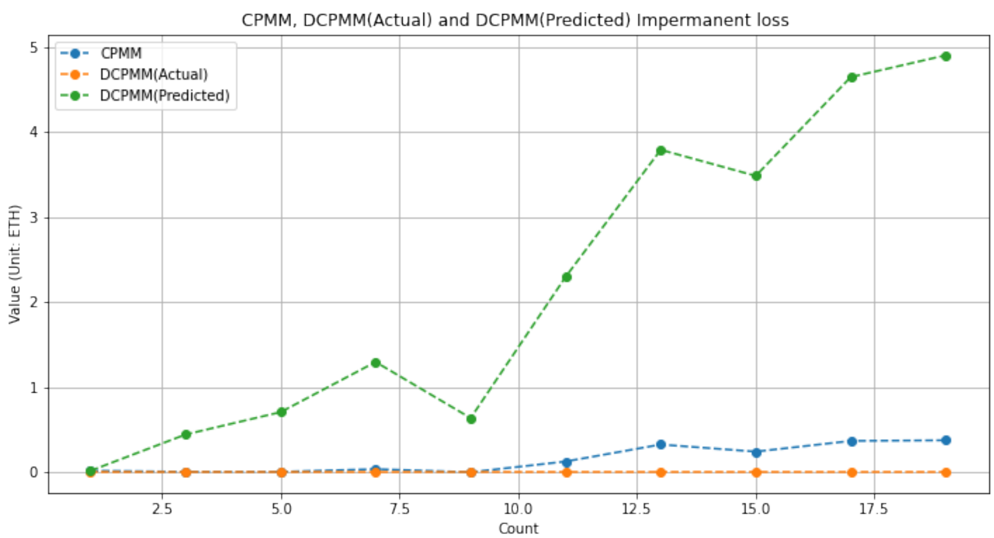

FIGURE 10 CPMM, DCPMM(Actual) and DCPMM(Predicted) Impermanent loss

5.2.6 Discussion on the simulation result

As you can see, it is not difficult to find that the impermanent loss of DCPMM(prediction) are worse than others. Price prediction is a hard task due to the effect of external environments such as social media, and news. Therefore, we couldn't obtain price values with perfect accuracy by using our prediction deep learning model to fulfill the price to reduce the impermanent loss. However, the DCPMM(actual) has better impermanent loss than the CPMM. If price prediction is not faultless, we will get the same result as shown above. Our system would make possible to provide price information without latency. That is to say, if performance of our prediction model be improved, we can implement decentralized exchange without impermanent loss.

V. Conclusion and Future Works

5.1 Conclusion

We proposed a new system regarding with dynamic constant product automated market maker. The new system uses deep learning based cryptocurrency price prediction and adjusts the curve based on the predicted result. To evaluate the performance of the system, we made a trading scenario and conducted experiments on CPMM, and DCPMM according to the scenario. The simulation results show that the changing curve following the market price is better than the fixed price curve but changing curve following the predicted price is worse. However, considering the results of the first simulation that used actual market price, if our prediction model's accuracy be improved, it is certain that our system has opportunities to reduce impermanent loss.

5.2 Future works

There are still limitations that will be addressed in future works. According to the simulation results, price prediction accuracy has a significant influence on the DCPMM's impermanent loss. Additional research is required to improve the prediction accuracy. Prediction accuracy of the deep learning model. First, our cryptocurrency price prediction model provides daily price prediction data. Because we used daily price data set as an input. Additional data should be collected using web scraper to provide more sophisticated time unit dataset. Second, we can use other methods to handle time series data. Recent findings on time series data, such as ARIMA, GRU and Transformer, have been published. It is expected that by using these methods, the model's performance will increase. Third, sentimental analysis can be applied with historical pricing data. Social media, for instance Twitter and Reddit, has a significant impact on cryptocurrency prices. Thus, recent researches use sentimental analysis to forecast price.

Another problem is that our price prediction model is centralized. It does not meet the blockchain's decentralization character. In the future, we can make the model decentralized using InterPlanetary File System (IPFS), federated learning, and computational oracle.

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