Stability Analysis of Market-Making Mechanisms for Decentralized Cryptocurrency Exchanges

***Abstract*—Several thefts of funds and from exchanges have raised concerns about the security of centralized digital currency exchanges, leading to the emergence of decentralized exchanges. However, the existing completely decentralized exchange mechanisms are inefficient, with high transaction costs hindering liquidity maintenance. This study analyzes the operational efficiency and stability of decentralized cryptocurrency exchanges. The predominant mechanism in existing exchange operations is the automated market maker, which eliminates the need for buyers and sellers to agree on prices and utilizes the inverse formula $X \times Y = K$. There are market stakeholders—such as investors, buyers, arbitrageurs, and trading platforms—perceive risks and opportunities differently amidst the high volatility of the cryptocurrency market. This paper discusses the merits, drawbacks, potential opportunities, and challenges associated with the mechanism. We also explore the market-time efficiency and methods for balancing stable slippage prices for buyers and arbitrage opportunities for arbitrageurs. Both static and dynamic conditions are considered.**

Keywords—cryptocurrency, decentralized, exchange, liquidity stability.

I. Introduction

Cryptocurrency exchanges can be broadly classified into two categories: centralized and decentralized. Centralized exchanges currently dominate the trading market [1]. Decentralized trading centers offer customers automated peer-to-peer (P2P) cryptocurrency transaction services. Malamud and Rostek [2] emphasize that any P2P exchange can constitute a decentralized transaction, which is the transaction center of aggregated transactions. Conventional centralized exchanges, such as banks and stock markets [1], differ from decentralized exchanges in several key aspects: 1) backend data are stored on a blockchain, 2) transactions are automatically executing without human intervention, 3) exchange rules take the form of smart contracts [3], 4) trading partners are unknown to each other and trade globally, and 5) no regulatory assurance is provided. Decentralized exchanges allow inventors to retain funds, enhancing personal production protection and reducing the money spent on fees charged by intermediaries. However, the emergence of decentralized exchanges poses challenges, with most exchanges not requiring identity verification or registration.

Centralized exchanges typically employ order book models [4] wherein buyers and sellers can customize their orders. Buyers aim to acquire assets at the lowest price, whereas sellers aim to sell them at the highest price. Therefore, a buyer and a seller must reach a consensus on the price to complete a transaction. Transactions occur in two scenarios: when the buyer raises their bid or when the seller lowers the price to sell. If no party is willing to rebid, the transaction stalls, necessitating the involvement of market makers. A market maker is an entity that facilitates transactions and accepts buy and sell orders, thereby providing liquidity [5] and enabling customers to trade without waiting for a counterpart to appear. Unlike centralized exchanges, blockchain uses the order book model, which results in substantial gas fees [6], [7], [8]. Decentralized exchanges address this issue by employing liquidity pools.

Automated market makers (AMMs) are decentralized exchange protocols that use mathematical formulas to price assets [9], [5], [10]. Unlike traditional exchanges with order books [4], an AMM uses an algorithm to price an asset; this reduces the blockchain load and prevents excessive on-chain fees. The operation mode of an AMM is similar to that of order book exchanges, and trading pairs are available, such as ETH/USDT (Ethereum/US Dollar of Tether) [10]. However, instead of engaging in transactions with other customers, AMM transactions are executed through P2P interactions with smart contracts.

Decentralized exchanges rely on liquidity pools, defined as pools of tokens that are locked in smart contracts and facilitate transactions by providing liquidity for customers [5], [11]. The decentralization and liquidity associated with these pools generate arbitrage opportunities, attracting arbitrageurs to perform reverse operations, thereby balancing the pools. Some trading centers adopt a static pricing mechanism expressed using the inverse formula $X \times Y = K$, where X and Y represent two types of cryptocurrencies and K is a constant value [12], [10]. The cost of the blockchain operation is low from the investor's perspective, but the exchange price increases with the transaction volume to maintain the constant value of K. This dynamic attracts speculators to observe arbitrage, ensuring the liquidity pool's equilibrium between the two types of cryptocurrencies. This paper proposes a dynamic pricing scheme for reducing the number of arbitrage opportunities arising from a transaction volume while maintaining liquidity conditions.

A liquidity pool involves two tokens and is a novel market for trading pairs. The formula for each pool is diverse. For example, a prevalent formula is $X \times Y = K$, where X represents the quantity of a specific token (e.g., Ether) in the liquidity pool (e.g., the Uniswap 2.0 decentralized exchange [13]), and Y is the amount of a stablecoin (e.g., USDC) [14], [15]. K is a constant, meaning that the total liquidity of the flow cell is always the same. This formula bestows limitless liquidity upon the liquidity pool, allowing customers to trade at their convenience without the need to wait on buyers and sellers. When a new liquidity pool is established, the initial liquidity provider (LP) sets the initial price in the pool, ensuring that the two assets in the liquidity pool have equivalent value. If the initial price deviates from the market price, an arbitrage opportunity is generated, risking the funds of the LPs. LPs who join the fund pool later are also exposed to this risk. Analyzing this risk and stability is a primary objective of this study.

LPs receive a distinct token reflecting the percentage of liquidity they have contributed. When transactions occur in a liquidity pool, the associated fees are distributed proportionally among all LP token holders [10]. When an LP withdraws their liquidity funds, its LP tokens must be destroyed so that the price can be adjusted through a deterministic algorithm. Funds injected by LPs into the liquidity pool serve as a fund that enables traders to engage in transactions. LPs earn transaction fees within their liquidity pools as compensation for providing liquidity to the decentralized exchange pools. For example, imagine a Uniswap LP deposits two tokens, 50% ETH and 50% USDC, in the ETH/USDC pool [13]. Anyone contributing funds to the liquidity pool can become a market maker, and the rewards are determined by the contract (e.g., a 0.3% fee per transaction). The objective of the present work is to design a method of attaining liquidity with reasonable arbitrage, allowing for adjustments in the proportion of two tokens without requiring LPs or investors to deposit additional funds in the liquidity pool.

The formula $X \times Y = K$ is used to represent an inverse relationship between the amounts of two tokens on slippage [10]. Let Y be a stablecoin bound to the price of 1 USD; the price of X is equal to Y/X, which increases in accordance with the relation $K/(X - b)$ when the exchange quantity b increases. This, in turn, attracts arbitrageurs to balance the price and the values of X and Y through reverse operations. This study devises exchange formulas with self-adjustment mechanisms that can balance the amounts of slippage and arbitrage.

Taking the formula $x \times y = k_1$ as the benchmark for enhancement, the quantities of two cryptocurrencies are denoted x and y, respectively. The product of the quantities of the two currencies is k_1, and the initial fund injection determines the value of k_1. The formula $(x + \Delta x) \times (y - \Delta y) = k_1$ is used to calculate the amount Δy or the amount Δx needed to be paid to buy Δy when Δx amount of X coins is used to purchase Y coins. The transaction price is determined from the ratio of Δx and Δy.

Researchers have proposed alternative formulas such as $x^2 \times y^2 = k_2$, the square formula $x^{0.5} \times y^{0.5} = k_3$, and the summation formula $X + Y = K$; however, they have not elucidated the effect of these formulas. The summation formula with zero slippage, although theoretically appealing, is impractical and fails to provide unlimited liquidity, rendering it unsuitable for use in an independent decentralized exchange application. This study scrutinizes the aforementioned formulas in various scenarios to assess their effects on price stability and liquidity from the standpoint of stakeholders (buyers, sellers, marketers, arbitrageurs, and platform operators), all within the context of decentralized finance (DeFi) operations. Two primary scenarios are examined: 1) Static price changes (considering changes solely within the liquidity pool): When the price in the liquidity pool changes in accordance with a static mathematical equation, such as those employed by Uniswap [13] and Curve [10], the stability of the calculation formula influences the behaviors of the four types of stakeholders. 2) Dynamic price changes (encompassing external market price fluctuations): LPs observe market prices through the oracle method to reflect external price changes, which affect the linkage relationship between prices in the LP. This effect is compared with the static price state. Accordingly, we compare the dual cryptocurrency trading calculation formula with the algorithmic stable cryptocurrency trading mechanism in terms of the stability, exchange efficiency, and transaction handling fees of transactions between two cryptocurrencies.

This study devises a novel formula, $(x + m_i) \times (y + n_i) = k_i$, that can enhance price stability and balance differential pricing and liquidity. The rationale underlying this formula is that a substantial k_i value yields a stable price. The core concept behind the proposed formula and adjustment schemes is to expand the exchange pool size, ensuring a stable exchange rate with small amounts of x and y. The variables m_i and n_i are used to control the smoothness of the exchange rate; they are set to $|I|$ pairs to utilize the feature of the larger pair variables m_i and n_i to lower slippages of the price. Different pairs of m_i and n_i result in different levels of differential pricing. We propose a squeeze method for identifying a near-optimal (m_i, n_i) pair that provides an arbitrage rate of at least R to maintain liquidity when the quantity of x is sold out to less than x/θ. Consequently, the DeFi cryptocurrency exchange rate is stable, and the price is automatically adjusted on the basis of the market price. Several DeFi protocols, including Uniswap and Curve, are available for customers to buy or sell tokens; these protocols employ an automated liquidity protocol and smart contracts [3], [16].

The academic contributions of the present research are as follows:

- A comparative analysis is performed on how various roles, the processing volume, and the transaction efficiency in a cryptocurrency exchange are affected by multiple calculation formulas.
- This work proposes a new scheme with calculation formulas that can maintain stability and liquidity while accommodating differential pricing in decentralized exchange transactions.

Additionally, this research makes the following practical research contributions:

- The proposed exchange formula can serve as a reference for the development of decentralized exchanges. Under the limitation of blockchain fees (such as gas fee set by currency Ether), it offers a small burden of calculation processing to solve the problem of excessive transaction costs while minimizing transaction friction costs.
- The utility of decentralized algorithmic exchanges is established, and algorithmic formulas and smart contracts are formulated that are tailored to diverse market requirements, thereby enhancing operational efficiency in trading centers.

The subsequent sections of this paper are organized as follows: Section II delves into related work; Section III outlines the research problem, solutions, and the adopted simulation procedures; Section IV presents experimental results and a discussion; and finally, Section V offers conclusions, limitations, and recommendations for future research.

II. Related Work

Numerous studies have emphasized the significance of decentralization in trading on decentralized exchanges, addressing factors such as search costs, counterparty risk, volatility, and information asymmetry [17], [18]. Aoyagi [19] reports that impermanent loss is the loss faced by liquidity pool investors when prices fluctuate; an LP must maintain equal value when allocating two currencies to the fund pool. For instance, if 1 ETH is priced at 3000 USDC, investors contribute to the ETH/USDC liquidity pool in a 1:3000 ratio. As prices shift, so does the pool's proportion. If the price of ETH rises to 4500, the value of an LP's net assets in the liquidity pool becomes less than the original fund pool's value. This study seeks to rectify this issue by making adjustments on the basis of market prices and introducing additional values for the two cryptocurrencies in the pool.

Stabilizing the price of cryptocurrencies involves minimizing price fluctuations. However, the market price, influenced by various factors, must reflect market dynamics. A dynamic AMM approach is proposed in this study in which a market price oracle is employed to align the pool price with the market price [5]. This approach eliminates arbitrage opportunities resulting from differences between pool and market prices. The study addresses the price changes induced by the liquidity mechanism when the market price is known. Stability is improved through an advanced formula and smart contract subject to decentralized operations and necessary liquidity.

Beyond fiat money, metal-anchored, and tied dollars, the blockchain system has stablecoins called algorithmic stablecoins [20]. These stablecoins are built upon a decentralized architecture through the inadequate mortgage mechanism, which has a complex and sophisticated design and strong customer confidence. In the case of the Luna cryptocurrency [21], the Terra algorithm requires two cryptocurrencies: the algorithm-stable USD coin called UST (Terra USD), and Luna coins, its collateral. Luna coins, with a guaranteed value exceeding 1 USD, are canceled for each UST generated, ensuring UST remains pegged to the USD. The system does not rely on USD reserves and instead leverages arbitrage trading of select cryptocurrency reserves, such as Bitcoin [22] and Luna coin. Customer confidence is crucial to transaction participation and currency value maintenance.

Arbitrageurs are theoretically crucial for aligning the prices of UST and Luna at 1 USD. As prices fluctuate, arbitrageurs can exchange directly, earning a spread by buying the lower-priced cryptocurrency. The stablecoin's value remains approximately 1 USD when arbitrageur participation is sufficient [21]. In a sense, the project creates value from thin air by incentivizing investment in other blockchain projects; stablecoins are generated without limit through mechanisms and algorithms. This research analyzes the UST stablecoin crash event to identify defects in algorithmic stablecoins and propose improvement methods.

Various AMM mechanisms are compared with the Uniswap 2.0 decentralized cryptocurrency exchange pool in this study [16]. The protocol has advanced to version 4.0. The main protocol of version 1 is a constant product market maker model, which is a benchmark used in comparisons in this work. Uniswap 2.0 supports the direct exchange of two tokens to minimize slippage, which is a goal of this work. Version 2.0 introduces the time-weighted average price, version 3.0 enables LPs to select a specific price range, and version 4.0 introduces time-weighted average market maker changes [23] relying on human operation. Uniswap 3.0's nonuniform liquidity formula is similar to that in previous versions but provides liquidity only within a specified exchange range. This study embraces the fully decentralized liquidity pool.

III. Problem Analysis

A. Transaction Stakeholders

This study considers the four stakeholders in transactions to be as follows: 1) investors, who provide funds for liquidity pools in decentralized exchanges; 2) arbitrageurs, who are specialists in identifying opportunities for arbitrage between decentralized and centralized exchanges; 3) platform operators or miners, who build decentralized exchange teams, attempt to enhance the customer experience, and earn transaction fees; and 4) customers, the typical users of cryptocurrency exchanges and who seek platforms with low transaction costs. The present analysis of the factors affecting stability and liquidity for a specific calculation formula is approached from the perspective of these four roles. Additionally, we introduce other calculation formulas to the discourse to pinpoint areas in which stability can be enhanced. Consequently, we propose a stability and liquidity formula that is termed virtual extension reverse proportion (VERP) and determine approximate parameters by using algorithms based on the squeeze function.

B. Static Price Impact Analysis

Based on historical records of Uniswap (2020–2021) DeFi center, which is the largest trading exchange, this study scrutinizes the operation of a liquidity pool supporting a decentralized ETH/USDC trading service. Assuming that the pool contains 80 000 ETH and 240 million USDC, the following preliminary analysis examines the impact of slippage on various stakeholders in this trading environment.

- Price change analysis from the perspective of investors:

  Suppose that the investment amount is equivalent to 10% of the liquidity pool (the investment and the two coins ratios have a linear relationship with the proportion of the pool). Regardless of price fluctuations, investors incur direct or indirect losses. As depicted in Fig. 1, the evaluation results illustrate the losses incurred at ETH prices of 2000, 3000, and 4000, respectively. These varying price fluctuations result in impermanent losses, with higher prices magnifying losses exponentially. The higher opportunity cost of rising price leads to higher amount of price increased. More favorable market conditions entail greater risk fluctuations, indicating poorer investment stability.

- Price change for arbitrageurs:

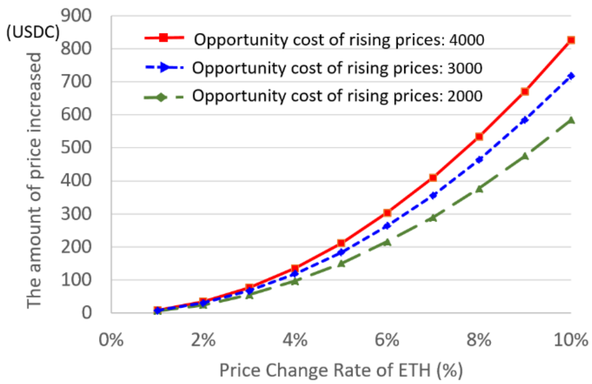

Fig. 1. Comparison of opportunity costs caused by the rate of change of the ETH price under various market prices.

Considering a Uniswap transaction fee of 0.3% and an average on-chain transaction cost (gas fee) of approximately 0.28% per transaction, the total transaction cost roughly amounts to ρ = 0.58%. The calculation process, accounting for fees in the formula $\gamma = 1 - \rho$, reveals an exponential increase in the ratio of the arbitrage amount to the price change under a changing ETH price, as illustrated in Fig. 2. Thus, greater price changes result in higher arbitrage availability.

The rate of return for arbitrageurs under a changing ETH price demonstrates a linear increase, indicating that not only does the amount of arbitrage increase linearly, but it also experiences exponential growth. Arbitrageurs have greater incentive to seek liquidity pools with higher price volatility.

- Slippage for customers:

Platform profits are primarily derived from two sources: handling fees and platform issuance. Most customers consider slippage and handling fees when participating in cryptocurrency exchange. The more liquid the funds in the pool, the smaller the slippage generated for a given volume of trading cryptocurrency. Fig. 3 shows the dynamic K values to follow market price observe the lower slippage rates (which are stable) that is compared with the constant K value to market prices, which is balanced by arbitrageurs. This work refers this result to design a dynamic formula to reflect the market prices.

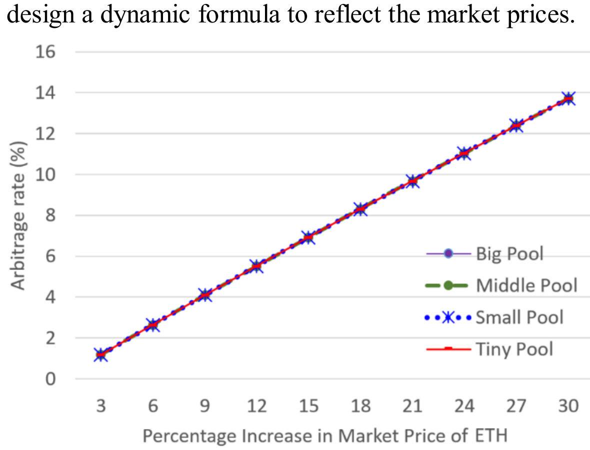

Fig. 2. Arbitrage caused by ETH price changes under various market prices.

- LP intervention in the liquidity pool

The price of a liquidity pool changes because of customer trades and market price fluctuations. LPs intervene to adjust the quantity of one of the two cryptocurrencies, aligning it with market prices or balancing prices through arbitrage. The LP intervenes and replenishes ETH in response to a transaction in the pool. Fig. 3 depicts the platform's effort to balance the liquidity pool promptly. The change in the price of ETH reflects the continuous addition of ETH to the liquidity pool, mitigating the increase in its price. The impact on the price of ETH is compared when the LP intervenes versus when it does not; intervention by the exchange results in a decrease in the proportion of ETH.

- Price slippage effect regarding liquidity pool size:

Customers selecting a decentralized exchange prioritize the size of the liquidity pool. The degree of slippage is directly proportional to the size of the pool. We assume that the average sizes of liquidity pools based on Uniswap, Curve, Pancakeswap, and Sushiswap are large, medium, or small, and we introduce even tiny pools for comparison. Fig. 4 presents an evaluation of price slippage from the customer's perspective across decentralized exchanges of different scales and for various purchase volumes. The price of ETH affects the size of the liquidity pool. The variable k reflects the pool size to denote big, medium, small, and tiny pools. The influence of liquidity pool size on slippage was obtained using the formula $X \times Y = K$. The evaluation results demonstrate that larger pools result in smaller slippage.

The smaller the price deviation generated in a transaction, the higher the price stability. Conversely, the larger the price deviation in the transaction, the poorer the price stability for the small and tiny liquidity pool. The exponential decrease in the price of coin ETH as the pool's proportion of ETH decreases. This trend is indicative of the trading dynamics within decentralized exchanges. We adopt this result to propose a method with two dummy variables to enlarge the size of exchange pool since the liquidity feature balances the price and make the trading quantity within a controlled amount of cryptocurrency. However, too large size of the exchange pool reduces the rate of arbitrage such that this work set a threshold of arbitrage rate to maintain liquidity.

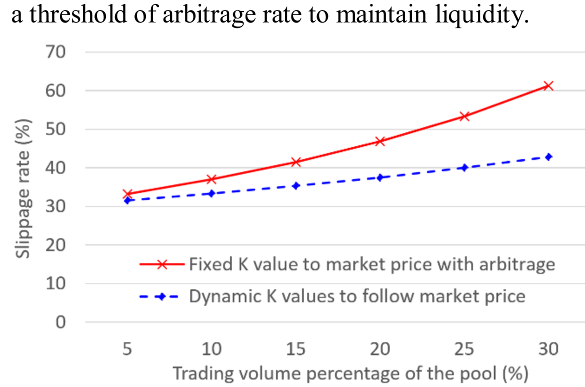

Fig. 3. Price changes when different proportions of ETH are withdrawn with a constant K value.

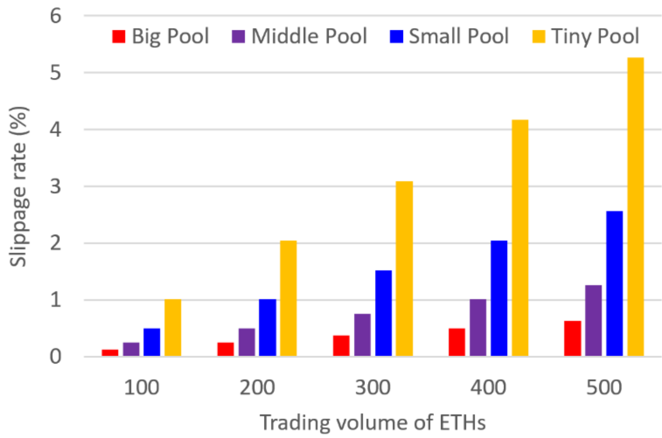

Fig. 4. Effect of liquidity pool size on slippage.

IV. Solutions

The stability of a calculation formula is indicated by the degree to which it maintains a consistent trading volume with minimal slippage. High stability means high exchange efficiency and low slippage for investors and customers. The results of sequential analysis have indicated that the stability of existing calculation formulas is insufficient. Consequently, we propose a stable price formula, VERP, which has the form $(X + m_i) \times (Y + n_i) = K_i$, where $i \in \{0, 1, 2\ldots I\}$ is the price section controller. Suppose the cryptocurrency exchange amount z falls between $e_i - 1$ and e_i. When the value z is small, the matched (m_i, n_i) is small, resulting in a high exchange price. Conversely, for a larger z, a larger pair (m_i, n_i) smoothens the price, offering lower value, but act as a log exchange pool. Additionally, liquidity considerations dictate that the remainder of the cryptocurrency be controlled with X/θ, where θ represents the proportion of the cryptocurrency. This setup aims to attract speculators to sell cryptocurrency X before its quantity falls below $1/\theta$.

A. Proposal Solution

Considering that the original quantities of cryptocurrency in the liquidity pool are x and y, the automatic balance formula $x \times y = k_0$ can be modified to $(x + m_I) \times (y + n_I) = k_1$. The formula for static prices is (1). The value of α is adjusted to transition from a small pool to a large pool while maintaining liquidity to ensure that the trading volume of X (or Y) is larger than x (or y); αx and αy represent phantom volumes to mitigate slippage.

$$(x + \alpha x) \times (y + \alpha y) = k_1 \tag{1}$$

The current price p_0 of the pool for cryptocurrency X is calculated as follows:

$$p_0 = y/x = (y + \alpha y) / (x + \alpha x) \tag{2}$$

Given an arbitrage rate of at least $R\%$ when the remainder volume of cryptocurrency X is larger than x/θ, Eq. (3) calculates the new price of X. The arbitrage rate is defined as the differential of the new and original prices divided by the original price. Then, the original price p_0 is substituted with $k_1/(x + \alpha x)^2$ to yield the final result.

$$\frac{\frac{k_1}{\left(x/\theta+\alpha x\right)^2}-p_0}{p_0}=\frac{\frac{k_1}{\left(x/\theta+\alpha x\right)^2}-\frac{k_1}{\left(x+\alpha x\right)^2}}{\frac{k_1}{\left(x+\alpha x\right)^2}} \tag{3}$$
$$=\frac{\left(x+\alpha x\right)^2}{\left(x/\theta+\alpha x\right)^2}-1=\frac{\left(1+\alpha\right)^2}{\left(1/\theta+\alpha\right)^2}-1\geq R\%$$

Dynamic market prices are considered using the extension formula $(x + \alpha x) \times (y + \beta y) = k_2$. This formula adopts a different ratio β for cryptocurrency Y (compared with the ratio α) to adjust the price in accordance with the market price. Suppose the current market price is p_2; then, (2) constrains variables α and β.

$$(y + \beta y) / (x + \alpha x) = p_2 \tag{4}$$

Formula (4) is then employed to obtain the β equation [(5)], where the two ratios of the X and Y cryptocurrencies are set as one variable α. The possible α values are iterated using (3) to control the arbitrage rate and liquidity. In this scenario, slippage is minimized when the market price is maintained. This formula shows the β value affected by the change of market price and α value such that we aim to determine α value.

$$\begin{aligned}&\left(x+\alpha x\right)\left(y+\beta y\right)=k_2\\&\Rightarrow\left(x+\alpha x\right)\left(y+\alpha y\right)\frac{p_2}{p_0}=\left(x+\alpha x\right)\left(y+\beta y\right)\\&\Rightarrow\frac{p_2\left(1+\alpha\right)}{p_0}=\left(1+\beta\right)\\&\Rightarrow\beta=\frac{p_2\left(1+\alpha\right)}{p_0}-1\end{aligned} \tag{5}$$

Using (5), the self-adjustment mechanism to satisfy market prices is iterated to yield (6). The variable α is correlated with the remainder ratio, original price, and market price. Once these variables are given, α and β are determined to determine the size of the liquidity pool that achieves low slippage with suitable liquidity. This formula helps us to search α value once the θ and arbitrage rate R are configured

$$\frac{\frac{k_2}{\left(x/\theta+\alpha x\right)^2}-p_0}{p_0}=\frac{\left(x+\alpha x\right)^2}{\left(x/\theta+\alpha x\right)^2}\frac{\left(y+\beta y\right)}{\left(y+\alpha y\right)}-1 \tag{6}$$
$$=\frac{\left(1+\alpha\right)\left(1+\beta\right)}{\left(1/\theta+\alpha\right)^2}-1=\frac{\left(1+\alpha\right)^2}{\left(1/\theta+\alpha\right)^2}\frac{p_2}{p_0}-1\geq R\%$$

B. Squeeze Method

Equations (3) and (6) are employed for increasing the X price when buyers exchange out an X coin (e.g., ETH). A higher price p_2 and lower remainder coin X with $1/\theta$ lead to a higher value that is a monotonically increasing function. To limit the arbitrage rate, the squeeze scheme, shown in Algorithm 1, is adopted to determine α and β. The threshold rate R is set on Line 13 to observe α and β values according to the rate r (Line 12).

```
Algorithm 1: Squeeze()
1   Given: the amount of coins x and y, arbitrage rate R, remainder
2          rate θ.
3   Output: α and β values for the proposed scheme.
4   init_price = y / x   // calculate the initial price in this DeFi pool
5   z = 1000000
6   new_price = init_price × m // Suppose the price is changed by m
7       // Suppose new_price >= init_price:
8   for i in range(1:z): //to search (α,β) values with squeeze method
9       α = i × 0.001
10      β = (new_price(1+i))/ init_price – 1 // referred to (3)
11      k = ((1+α) × x) × ((1+β) × y)
12      r = (k/pow(((x/θ) + (α×x)),2) - ((1+α)*y)/((1+α)*x))
            /(((1+α)×y)/((1+α)×x))
            // trading remaindering x/θ to calculate arbitrage rate r
13      if r <= R:
14        break
```

We iterate the α and β values into the trading evaluation scheme, as shown in Algorithm 2 Slippage(), to compare the rate of slippage with that achieved using the original formula and existing methods. The price is calculated based on the amount of *x_trade* to observe how much Y coin of *y_trade*, which is determined by the calculation formulas.

```
Algorithm 2: Slippage()
Given: the amount of x and y cryptocurrencies, a serial control
variable buy_amounts,
Output: slippage of X.
price = y_new / x_new
prices_new05 = []
m = αx
n = βy
k = (x+m) × (y+n)
for x_trade in buy_amounts:
  y_trade = ( k / (m - x_trade)) - (y+n)
  x_new = x - x_trade
  y_new = y + y_trade
  price = y_trade / x_trade
```

C. Comparison of Existing Solutions

Several calculation formulas are employed to enable the advantages and limitations of the proposed method to be determined. Weakness levels are considered, including severe slippage and external financial risk (e.g., incorporating temporary losses and short- and long-term volatility/volume correlation). The calculation formulas that are compared are as follows:

- *Inverse Ratio* (*IR*): $X \times Y = K_1$, the formula used in Uniswap 2.0. This idea is extended to 3.0 in practice.
- *Square Inverse Ratio* (*SIR*): $X^2 \times Y^2 = K$.
- *Square Root Inverse Ratio* (*SRIR*): $x^{0.5} \times y^{0.5} = K$.

V. Evaluation

This study compares the proposed formulas and algorithms with the original and existing methods.

A. Evaluation Case Design

To evaluate the stability and liquidity of the proposed schemes, three cases are designed:

- Case 1: The effect of the slippage rate on the trading volume of cryptocurrency X is examined. Slippage is evaluated under various trading volumes, and the aim is stability and buyer benefit while maintaining liquidity.
- Case 2: The effects of dummy variables α and β on static and dynamic prices and the size of the liquidity pool are investigated. The variable β is changed on the basis of α through (6). Thus, the relationship between α and the arbitrage rate (R) with various remainder rates ($1/\theta$) is evaluated.
- Case 3: The effects of liquidity and dummy variables on the remainder rate ($1/\theta$) and arbitrage rate (R) are investigated. Once the remainder rate $1/\theta$ and arbitrage rate R are fixed, the approximate values of α and β are determined and the slippage price is then evaluated according to the market prices.

B. Evaluation Results

Fig. 5 presents the results for Case 1, comparing the liquidity formulas. The IR, SIR, and SRIR formulas are found to result in similar outcomes in terms of slippage prices. In the proposed VERP scheme, larger values of m and n result in lower slippage prices, enabling control of these two variables to achieve stable prices. However, m and n cannot be given unlimited large values because this would violate the goal of liquidity.

Figs. 6 and 7 illustrates the effects of the dummy variables on static and dynamic prices for Case 2 evaluations, respectively. Smaller amount of remainder rates of X generally result in higher value α, but the higher arbitrage rate R maintains lower variable α to include smaller amount of dummy values so that the higher arbitrage rate R to attract arbitrage and balance the liquidity risk.

Fig. 8 shows the impact of slippage prices on the remainder rate $1/\theta$ and arbitrage rate R for Case 3. The proposed scheme keep in low the slippage rate and smooth. Lower slippage prices are discovered for lower remainder rates. A low remainder rate results in high liquidity risk, necessitating a high arbitrage rate R. Therefore, the remainder and arbitrage rates must be controlled to ensure liquidity and prevent potential shortages in the cryptocurrency pool for future exchange transactions. The ratio of variable α is unchanged amidst changes in the price of cryptocurrency X and the variable β adjusted based on the market price to affect the liquidity pool size.

C. Discussion

Although the original scheme results in a high arbitrage rate, customers may prefer buying in batches to avoid significant slippage when exchanging large quantities. Each batch with a small quantity allows customers to wait for the price to return to a reasonable level, potentially resulting in a lower overall arbitrage rate than that for the proposed stable slippage method.

The proposed method provides competitive slippage prices for small pools and reflects the market price through dummy variables. It means too many coins put in the pool might not trade with liquidity mechanism. Because trading quantity can be configured with the arbitrage rate. However, the arbitrage rate should be sufficiently high to attract arbitrageurs for reverse operations and maintain liquidity before the amount of any one type of cryptocurrency in the pool becomes too low.

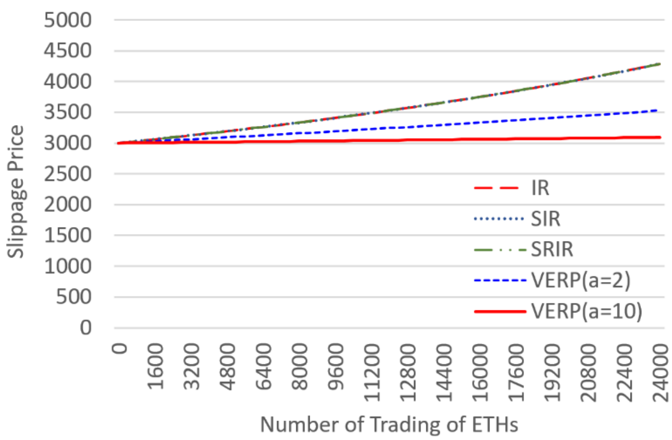

Fig. 5. Effect of liquidity pool size on slippage (Case 1).

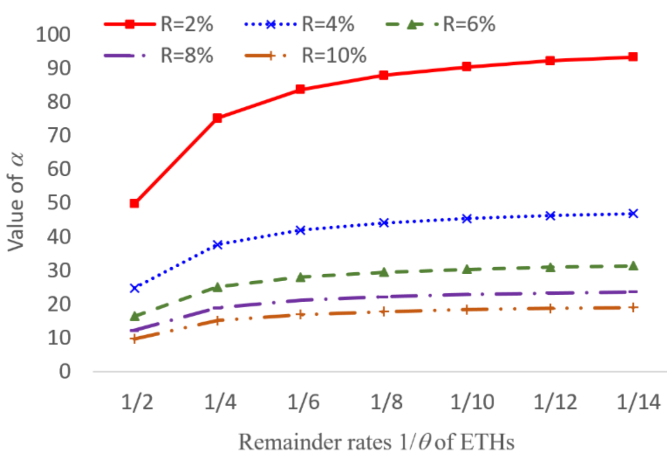

Fig. 6. Effects of dummy variables on static and dynamic prices (Case 2).

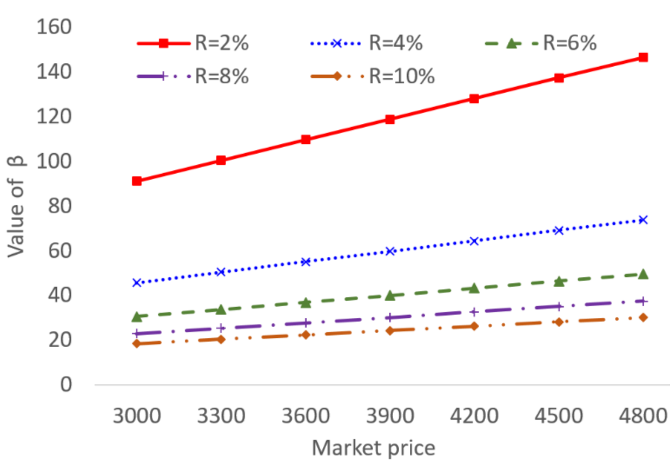

Fig. 7. Effects of dummy variables on static and dynamic prices (Case 2).

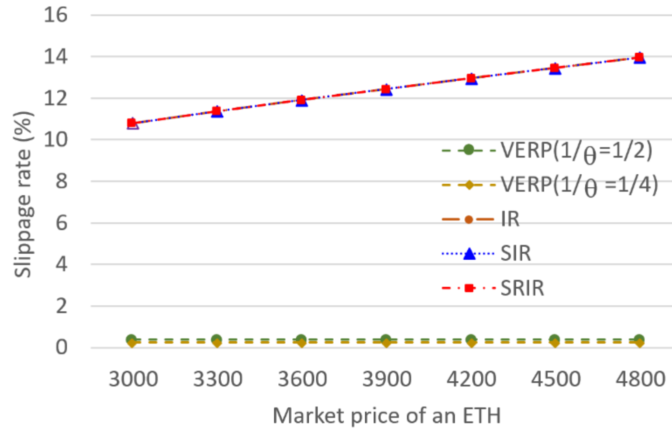

Fig. 8. Effects of slippage price on the remainder and arbitrage rates (Case 3).

The designed scheme is straightforward; it incorporates two additional variables, m and n, which are controlled with α and β, with addition. The threshold arbitrage rate R for price changes and adjustment ratios can be calculated in advance; thus, the proposed method keeps gas fees low.

VI. Conclusions

This study analyzed decentralized cryptocurrency exchanges and how liquidity with stable prices for general customers can be achieved. A balanced method was established that can dynamically adjust the size of the liquidity pool by using dummy variables and thereby achieve equilibrium between slippage and arbitrage rates. This study evaluated the effect of slippage price through a series of experiments and demonstrated that the proposed method achieves its objectives and outperforms existing schemes in terms of slippage price stability. Furthermore, we identified approximate combinations of dummy variables that reflect market prices while achieving stable prices and liquidity goals.

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