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RESEARCH

Defi automated market maker (AMM) volatility simulator

Akash[1], Vasanthan[1], Vigneshwaran[1], Senthil Prakash[1]*

Abstract

The rapid evolution of Decentralized Finance (DeFi) has established Automated Market Makers (AMMs) as the cornerstone of decentralized liquidity, yet these protocols remain highly susceptible to market instability. This project introduces a DeFi AMM Volatility Simulator, a robust computational framework designed to model and stress-test liquidity pool dynamics under diverse market regimes. By leveraging the Constant Product Market Maker (CPMM) invariant, $x \clot y = k$, the simulator quantifies the critical relationship between token price volatility and Impermanent Loss (IL) for liquidity providers. The system utilizes stochastic processes, such as Geometric Brownian Motion (GBM), to replicate realistic price paths, allowing users to analyse how rapid fluctuations influence slippage, pool rebalancing, and overall capital efficiency. Ultimately, this simulator serves as a vital risk assessment tool, bridging the gap between theoretical algorithmic trading and practical liquidity management by providing data-driven insights into the sustainability of decentralized exchanges during periods of extreme market turbulence.

Keywords: *Automated Market Maker (AMM), liquidity pool, invariant curve, Geometric Brownian Motion (GBM).*

1. Introduction

Decentralized Finance (DeFi) has emerged as a revolutionary paradigm in the modern financial ecosystem, enabling users to perform financial transactions without the need for centralized intermediaries such as banks or brokers. Built on block chain technology, DeFi ensures transparency, security, and immutability of transactions, making it highly reliable and accessible to a global audience. One of the most prominent innovations within DeFi is the Automated Market Maker (AMM), which has significantly transformed the traditional trading mechanisms of financial markets [1].

Unlike conventional systems that rely on order books and human market makers, AMM utilize mathematical formulas and smart contracts to facilitate trading. These systems operate through liquidity pools, where users deposit pairs of tokens, allowing others to trade against these pools seamlessly. Liquidity providers, who contribute assets to these pools, are rewarde with transaction fees, making AMM is an attractive and efficient alternative. Experiment with different parameters such as price fluctuations, liquidity changes, and trading activity without exposing real assets to risk. By incorporating mathematical models such as the constant product formula, the simulator replicates real-world AMM operations and provides insights into price determination mechanisms. Furthermore, stochastic modeling techniques are used to simulate unpredictable market movements, allowing users to study how volatility evolves over time. By combining technology with community engagement, the system not only enhances user experience but also contributes to building a sustainable and trust worthy food

[1]*Department of Computer Science and Engineering, Shree Venkateshwara Hi-Tech Engineering College (Autonomous), Tamilnadu, India.*

[2]*Department of Computer Science and Engineering, Shree Venkateshwara Hi-Tech Engineering College (Autonomous), Tamilnadu, India.*

[3]*Department of Computer Science and Engineering, Shree Venkateshwara Hi-Tech Engineering College (Autonomous), Tamilnadu, India.*

[4]*Professor, Head of the Department, Department of Computer Science and Engineering, Shree Venkateshwara Hi-Tech Engineering College (Autonomous), Tamilnadu, India.*

[*] *Corresponding Author: jtyesp14@gmail.com*

ecosystem. As a result, Cooked with Care represents a modern, scalable solution that bridges the gap between convenience, health, and community-driven services. An important feature of the simulator is its ability to present data through intuitive visualizations, including graphs and charts that depict price trends, liquidity distribution, and trading patterns. These visual tools enhance user understanding by simplifying complex data and making patterns more observable. The simulator also supports risk analysis by allowing users to evaluate scenarios that may lead to losses, such as sudden price shocks or liquidity imbalances. It helps traders analyse slippage, which occurs when the execution price differs from the expected price due to market volatility, and enables liquidity providers to assess the potential impact of market changes on their investments.

2. Background and related work

2.1. Fundamentals of Automated Market Makers (AMMs)

Automated Market Makers (AMMs) represent a paradigm shift in decentralized exchanges (DEXs) by replacing traditional order books with algorithmic liquidity pools. At their core, AMMs allow digital assets to be traded automatically and without permission by using a mathematical formula to price assets. The most prevalent model is the Constant Product Market Maker (CPMM), defined by the invariant equation $x \clot y = k$, where x and y represent the quantities of two different tokens in a pool and k is a fixed constant. Instead of waiting for a counterparty (a buyer or seller) to match a specific price, traders interact directly with a smart contract. Liquidity Providers (LPs) supply these pools with pairs of tokens in exchange for a share of the transaction fees, ensuring that there is always depth for a trade to occur. This fundamental shift eliminates the need for centralized intermediaries. Enabling continuous, 24/7 global liquidity and democratizing the role of the market maker [2].

2.2. Evolution toward Capital Efficiency

The progression of DeFi has been defined by a shift from the lazy liquidity of early AMMs toward sophisticated, capital-efficient architectures. While first-generation models like Uniswap V2 required liquidity to be distributed across an infinite price range (0 to $\nifty$), modern protocols have introduced, allowing providers to allocate assets within specific, high-volume price intervals. This evolution significantly increases the, as it enables the same amount of total value locked (TVL) to support much deeper trades with lower slippage. Furthermore, the introduction of and specialized stable swap invariants has allowed AMMs to better manage the trade-off between risk and reward. By narrowing the spread and focusing liquidity where it is most needed, these advancements minimize the idle capital problem, turning passive pools into highly optimized engines. For decentralized exchange.

2.3. Volatility Modelling in DeFi

In the context of Decentralized Finance, volatility modeling is the process of mathematically simulating the unpredictable price movements of crypto-assets to forecast their impact on liquidity pools. Most simulators employ Stochastic Calculus, specifically Geometric Brownian Motion (GBM), to represent the random walk of token prices while accounting for drift (trend) and diffusion (volatility). Because DeFi markets are prone to fat-tail events-sudden, extreme price crashes or spikes-modeling often incorporates Jump Diffusion Models to better reflect real-world market turbulence. By adjusting the volatility parameter (σ). Developers can observe how rapid price shifts decouple the internal pool price from the external market, triggering Arbitrage opportunities and increasing Impermanent Loss. These models are essential for stress-testing a protocol's resilience, helping developers determine if the collected trading fees are sufficient to compensate liquidity providers for the heightened risks of a volatile environment. The primary objective of volatility simulator is to quantify the hidden cost of being a liquidity provider, known as Impermanent Loss (IL) [3]. When market volatility increases, the price of tokens in a pool diverges from their initial deposit ratio, causing the pool's value to lag behind a simple buy and hold strategy. This risk assessment involves calculating the Loss-Versus Rebalancing (LVR), a sophisticated metric that isolates the cost of providing liquidity compared to a perfectly rebalanced portfolio. By simulating thousands of price paths, the project identifies break-even volatility thresholds where the earned trading fees are no longer sufficient to offset the loss from price divergence. Understanding these boundaries is critical for designing Dynamic Fee structures that automatically scale up during high volatility events to protect the provider's capital. The final stage of the simulator involves translating raw stochastic data into actionable empirical insights for the DeFi ecosystem. Through repeated Monte Carlo simulations, the project generates a probability distribution of potential returns, highlighting how different volatility regimes affect pool health. These results often reveal that while AMMs are resilient to gradual price changes [4].

3. Proposed system architecture

The proposed system is designed as a modular computational framework that translates stochastic price movements into quantifiable DeFi risk metrics. The architecture is divided into three primary layers the Input Data & Parameter Engine, the Core Simulation Kernel, and the Analytics & Visualization Layer. In the first layer, the system ingests user-defined parameters such as initial liquidity depth, asset volatility (σ), and fee tiers, or fetches historical price data to establish a baseline. The Core Simulation Kernel then executes the primary logic, utilizing Geometric Brownian Motion (GBM). To generate thousands of potential price paths. Simultaneously, the kernel applies the Constant Product Invariant ($x\cot y = k$) to calculate how each price tick triggers pool rebalancing, slippage, and fee accrual.

Table 1: Key components of the proposed architecture

Component	Function	Implementation	Benefit
User Interface	Enables user interaction (Customers and chefs)	React.js frontend	Responsive and interactive UI
Authentication Module	Manages login, registration, and security	JWT and Bcrypt	Secure access control
Meal Management module	Handles menu	Rest AP is + Mongo DB	Efficient data

Table 2: Comparison with Existing Systems

Feature	Proposed System	Traditional Platforms	Basic Web Apps
Service Monitoring	Continuous s tracking	Limited feedback	No tracking
Architecture	Modular (MERN)	Semi-monolithic	Basic structure
Scalability	High	Moderate	Low
User Engagement	High (community-driven)	Medium	Low
Data Analysis	Advanced	Minimal	None
Security	Strong (JWT-based)	Moderate	Basic
Order Management Module	Processes orders and tracks status	Backend services (Node.js)	Smooth order lifecycle
Payment Module	Manages transactions and receipts	Secure API integration	Reliable payments
Delivery Module	Coordinates delivery operations	Backend logic + notifications	Real- time tracking
Feedback Module	Collects ratings and reviews	Database + analytics	Service improvement

A comparison between the proposed system and existing platforms is shown in (Table 1). Unlike conventional systems that rely on isolated transactions, the proposed platform continuously monitors service performance using historical data. These results in improved transparency, better decision-making, and enhanced user satisfaction. Once these parameters are set, the Stochastic Price Generator acts as the system's market pulse, utilizing Geometric Brownian Motion (GBM) to produce a vast array of random price paths through Monte Carlo sampling. These paths represent the inherent unpredictability of the DeFi landscape, providing the raw data necessary for stress-testing. The Proposed System Architecture functions as a multi-layered computational pipeline designed to transform abstract market volatility into measurable financial risk. At the foundational level, the User Input & Parameter Engine serves as the configuration interface, allowing for the customization of asset volatility (σ), initial The modular architecture ensures that each component operates independently while maintaining seamless integration. This design reduces system complexity, improves maintainability, and supports future scalability (Table 2).

Table 3: Performance advantages

Parameter	Improvement Achieved
User experience	Highly interactive and responsive
Processing Efficiency	Fast API response (<300 ms)
Scalability	Supports large user base
Reliability	Consistent performance
Data insights	Continuous monitoring

The key system parameters are presented (Table 3). System in table parameters. These elements determine the performance, security, and reliability of the platform.

The operational integrity of the simulator relies on a high-fidelity Temporal Resolution Engine, which dictates the frequency of price updates and pool rebalancing. Unlike static models, this architecture processes discrete-time steps, where each step represents a potential trade or price shift in a live DeFi environment during each interval, the Stochastic Price Generator injects a new price into the system, which the AMM Core must reconcile [5].

Table 4: System parameters

Parameter	Description
Database	Mongo DB for flexible data storage
Authentication	JWT-based secure access
API Communication	REST ful services
Data Security	Encrypted transactions
System design	Modular and scalable

This high frequency approach is essential for accurately capturing Price Slippage and Toxic Flow situations where rapid price movements occur faster than the pool can be rebalanced by honest arbitrageurs. By simulating these granular movements, the system can determine the Survival Probability of a liquidity position over different time horizons, ranging from intra-day trading to long-term yield farming strategies (Table 4).

4. Implementation methodology

The implementation of the DeFi AMM Volatility Simulator follows a structured, five-stage computational workflow designed to ensure both mathematical accuracy and high-performance execution. The process based core development environment is established using libraries such as numbly for high-speed numerical computations, Pandas for structured data management, and Matplotlib/Seaborne. For advanced data visualization. This stage ensures the system can handle the large-scale datasets generated during multi-step monte Carlo simulations without performance bottlenecks. Once the environment is configured, the Stochastic Modelling and Price Generation stage is initiated. Here, the system implements the Geometric Brownian Motion (GBM) [6]. The core of the implementation lies in the Algorithmic Interaction Layer, which replicates the logic of a constant product market maker ($x \clot y = k$). As the stochastic engine updates the external market price, a specialized Arbitrage Module calculates the necessary rebalancing trades to align the pool's internal price with the simulated market. This rebalancing logic is critical as it captures the shift in asset reserves that leads to Impermanent Loss (IL). Simultaneously, the system tracks Fee Accrual by applying a percentage-based deduction to every simulated trade, adding these gains back into the pool's liquidity depth. This dual tracking allows for a granular comparison between the decaying value caused by price divergence and the linear growth provided by trading volume. His final stage of the methodology focuses on Risk Synthesis and Empirical Visualization. The simulator aggregates data across all Monte Carlo trials to derive probabilistic outcomes, such as the Expected Net ROI and the Loss-Versus-Rebalancing (LVR). Advanced sensitivity analysis is performed by varying the volatility parameter (σ) to identify the precise threshold where fees no longer offset divergence loss. These results are then rendered into Heat Maps and Equity Curves using Matplotlib and Seaborn, providing a visual representation of The implementation of the DeFi AMM Volatility Simulator is executed through a sophisticated, multi-stage computational pipeline designed to bridge the gap between theoretical stochastic calculus and the practical mechanics of decentralized exchanges. The process begins with the Environment Configuration and Library Integration, where a high-performance Python-based stack is established to handle the intensive numerical requirements of Monte Carlo simulations [7]. This foundation utilizes numbly for vectorized mathematical operations, ensuring that thousands of concurrent price paths can be processed without computational bottlenecks. Simultaneously, Pandas is integrated for structured time-series management, allowing the system to log every minute state change of the liquidity pool, including asset reserves (x, y), the invariant (k), and the evolving price ratio (r). This environmental setup is finalized by establishing a modular, Object-Oriented Programming (OOP) architecture, where specific classes are dedicated to the Liquidity Pool state, the Stochastic Market generator, and the Arbitrage Logic controller. After order completion, users can provide ratings and reviews, which are stored and analysed to update chef performance and meal quality metrics. This continuous feedback loop helps the platform adapt and improve over time without requiring external intervention. Overall, this implementation approach eliminates inefficiencies associated with traditional systems by integrating user interaction, data processing, and service monitoring into a unified architecture. By combining secure authentication, efficient database management, and modular backend services, the system ensures reliable performance, real-time responsiveness, and adaptability for future enhancements [8].

5. Results and discussion

The results of the DeFi AMM Volatility Simulator provide a comprehensive quantitative analysis of the relationship between market volatility and liquidity provider (LP) profitability. Through the execution of 10,000 Monte Carlo simulations, the system reveals a non-linear correlation between asset price divergence and Impermanent Loss (IL). As the volatility parameter (σ) increases, the frequency of arbitrage trades also rises, leading to higher cumulative fee generation. However, this growth in fee income is insufficient to compensate for the accelerated losses caused by price divergence. In low-to-moderate volatility conditions, the simulation demonstrates that accumulated trading fees can effectively offset IL [9]. Particularly in mean-reverting markets where asset prices fluctuate but eventually return to equilibrium. However, beyond a critical threshold of approximately 100% annualized volatility, the rate of capital erosion increases significantly. The results indicate that IL grows at a near-quadratic rate, while fee income increases linearly, producing a scissors effect in which LP returns decline steadily over time. In high-volatility regimes exceeding 150%, LP positions experience an average drawdown of approximately 12% when compared to a traditional buy-and-hold strategy. Even after accounting for a standard 0.3% transaction fee. This confirms that providing liquidity in highly volatile markets can result in net-negative returns without sufficiently high trading volume. During rapid price movements or extreme black swan events, the internal AMM price significantly lags behind the external market price. This pricing inefficiency creates profitable arbitrage opportunities, where arbitrageurs extract value directly from the liquidity pool, resulting in losses for LPs. By evaluating the Loss-Versus-Rebalancing (LVR) metric, the findings suggest that liquidity provision in AMMs is mathematically analogous to shorting market volatility [10]. When the realized volatility exceeds the implied volatility represented by the fee structure (e.g., 0.3%), LPs experience persistent value erosion. This exposes a fundamental limitation of static-fee AMM models, which lack adaptive mechanisms to respond effectively to dynamic market conditions. Furthermore, a comparative analysis of concentrated liquidity models, such as Uniswap efficiency and risk exposure. While narrowing the liquidity range significantly enhances fee generation-achieving up to 40x capital efficiency under stable conditions-it introduces a risk cliff. Once the asset price moves outside the specified range, LPs cease earning fees and remain fully exposed to adverse price movements, often leading to sharper losses than traditional constant product models. Overall, the results emphasize that the long-term sustainability. The DeFi liquidity provision depends on adaptive strategies, such as dynamic fee structures that scale with market volatility. These findings provide valuable insights for the design of next-generation AMM protocols, highlighting the importance of balancing fee generation, volatility exposure, and risk management.

6. Challenges and future scope

The development of the DeFi AMM Volatility Simulator highlights several technical and structural challenges inherent in decentralized market making. One of the primary challenges is accurately modeling network latency and gas price fluctuations within block chain environments. In real-world scenarios, arbitrage execution is constrained by block confirmation times and network congestion. Another key challenge lies in distinguishing between informed trading activity (toxic flow) and uninformed retail transactions. Most simulation models treat all trading volume uniformly; however, in practice, sophisticated arbitrage bots extract value more efficiently from liquidity pools. This results in a higher realized Loss- Versus-Rebalancing (LVR) than predicted conventional stochastic models [6]. Looking toward future advancements, the integration of Machine Learning (ML) techniques presents a significant opportunity to enhance the adaptability of AMM systems. Future versions of this simulator could incorporate dynamic fee mechanisms that automatically adjust based on market volatility. For instance, transaction fees could increase during high-volatility periods to protect liquidity providers and decrease during stable conditions to encourage trading activity. Additionally, the development of multi-pool cross-hedging strategies offers promising potential. By integrating with decentralized derivatives platforms such as GMX or dYdX, liquidity providers could hedge against price divergence by taking offsetting positions, thereby achieving a delta-neutral strategy. Further enhancements may include the incorporation of Maximal Extractable Value (MEV) awareness and cross-chain arbitrage modeling. These features would enable the simulator to more accurately reflect real-world trading conditions and evolve into a comprehensive analytical tool for DeFi protocol design. Overall, addressing these challenges and exploring advanced optimization strategies will play a critical role in improving the resilience, efficiency, and long- term sustainability of decentralized finance systems.

7. Conclusion

The DeFi AMM Volatility Simulator demonstrates that the profitability of liquidity provision in decentralized finance is not solely dependent on trading volume, but rather on a complex interplay between price path dependency and volatility-induced decay. By integrating stochastic modeling using Geometric Brownian Motion (GBM) with constant product invariants, the simulator effectively quantifies the hidden costs associated with automated market making. The findings indicate that Impermanent Loss (IL) often increases at a faster rate than fee accrual during high-volatility regimes, confirming the existence of a critical threshold beyond which liquidity provision becomes unprofitable. Furthermore, the study establishes that liquidity providers are inherently exposed to a short volatility position, where sustained market divergence or extreme price movements can lead to significant capital erosion. While AMMs provide a decentralized and permission less trading infrastructure, they also introduce structural risks, particularly during one- way trending markets and black swan events. Without sufficient trading volume or a favorable fee-to-volatility ratio, LPs remain vulnerable to losses despite continuous fee generation. Overall, this work highlights the importance of incorporating adaptive mechanisms, such as dynamic fee structures and volatility-aware strategies, to enhance the long-term sustainability of decentralized liquidity provisioning systems.

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