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THE POTENTIAL FOR REAL-TIME TESTING OF HIGH-FREQUENCY TRADING STRATEGIES THROUGH A DEVELOPED TOOL DURING VOLATILE MARKET CONDITIONS

Abstract

This study presents a method for testing high-frequency trading (HFT) for algorithms on GPUs using kernel parallelization, code vectorization, and multidimensional matrices. The research evaluates HFT strategies within algorithmic cryptocurrency trading in volatile market conditions, particularly during the COVID-19 pandemic. The study's objective is to provide an efficient and comprehensive approach to assessing the efficiency and profitability of HFT strategies. The results show that the method effectively evaluates the efficiency and profitability of HFT strategies, as demonstrated by the Sharp ratio of 2.29 and the Sortino ratio of 2.88. The authors suggest that further study on HFT testing methods could be conducted using a tool that directly connects to electronic marketplaces, enabling real-time receipt of high-frequency trading data and simulation of trade decisions. Finally, the study introduces a novel method for testing HFT algorithms on GPUs, offering promising results in assessing the efficiency and profitability of HFT strategies during volatile market conditions.

1. INTRODUCTION

Market fear is a critical macroeconomic construct that requires in-depth and thorough monitoring even in normal circumstances due to its substantial nexus with critical financial assets (Ghosh, I., Sanyal, M. K., 2021; Bouri, E., et al., 2018; Just M., Echaust, K., 2020). In addition, it could be influenced by news, pandemics, etc.

Many studies have been conducted since the pandemic's beginning to assess its impact. During the ongoing COVID-19 timeline, Ghosh and Sanyal (Ghosh, I., Sanyal, M. K., 2021)

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used India VIX and 20-day rolling standard deviation of NIFTY returns to account for implied and historical volatility, respectively, and proposed architectures that can effectively predict them and serve practical, actionable insights. During the COVID-19 pandemic, Disli et al. (Disli, M., 2021) investigated the role of gold, crude oil, and cryptocurrency as a haven for traditional, sustainable, and Islamic investors. Park's paper examined how pandemic-induced market stress influenced the dynamic relationship between volatility and trading behavior variables (Park, B. J., 2022). Borgards et al. (Borgards, O. et al., 2021) investigated the overreaction behavior of 20 commodity futures based on intraday data from November 20, 2019, to June 3, 2020, focusing on the COVID-19 pandemic. Recent academic studies (Borgards, O. et al., 2021; Lin, B., Su, T., 2020; Adekoya, O. B., Oliyide, J. A., 2021; Salisu, A. A., et al., 2020; Ji, Q. et al., 2020; Wu, B. B., 2021) have also examined the impact of the COVID-19 pandemic on the commodity market. Several studies have demonstrated the relationship between commodities and commodities and other asset classes (Borgards O. et al., 2021).

While some authors focused on the market impact of the pandemic, others worked on model testing and improvements. Loh et al. (2022) proposed a complete end-to-end system for automated low-frequency quantitative trading in forex markets. They concluded that as market volatility rises due to the global pandemic, the momentum behind machine learning algorithms that can adapt to changing market conditions will grow even more robust (Loh, L. K. Y., et al., 2022). Tudor and Sova (Tudor, C., Sova, R., 2022) presented a novel decision-support system (DSS) for algorithmic trading and empirically tested it on two major crude oil markets. They discovered that DSS-based trading strategies can reduce and even eliminate losses during market downturns, including the outbreak of the COVID-19 pandemic (Tudor, C., Sova, R., 2022). Abedin et al. (Abedin, M. Z., et al., 2021) proposed a deep-learning ensemble approach. As a result, during the COVID-19 period, the prediction performance of the used model deteriorated.

Virgilioin (Virgilio et al., 2019) investigated the impact of high-frequency trading on the main market quality parameters. He summarized academic research on the role of HFT in minor and significant flash crashes. The summary demonstrates that almost all authors agree on the role of HFT in the Flash Crash and its alleged many minor variants (Virgilio, G. P. M., 2019, Bellia, M., et al., 2020) investigated the role of high-frequency trading during Flash crashes and discovered that HFTs do not improve market efficiency or liquidity during times of severe market distress. Finally, Ammar and Hellara investigated the impact of high-frequency trading (HFT) on the price volatility of Euronext-traded stocks (Ammar, I. B., Hellara, S., 2022). During intraday crashes, they discovered that rapid interactions between HFT algorithms result in high rates of order cancellations and simultaneous withdrawals of high-frequency traders from the limit order book (Ammar, I. B., Hellara, S., 2022).

However, it is worth noting that due to the proprietary and sensitive nature of HFT strategies and data, some specific details and methodologies employed by HFT firms may be kept confidential for competitive reasons. This can limit the availability of specific data sets or restrict the dissemination of proprietary trading algorithms (Hossain S., 2022). Additionally, high-frequency trading is a rapidly evolving field, and the pace of academic research may need help to keep up with the constantly changing landscape of HFT (Baron M., et al., 2019). This form of trading is extensively commercialized, and the employed strategies and ideal setups for high-frequency trading companies are kept confidential. Revealing insights into the optimal implementation of HFT and techniques to enhance decision-making speed would not only contribute to the advancement of trading strategies. However, it could also have applications in other scientific domains that deal with large-scale data analysis and rapid decision-making. Existing literature primarily offers methodologies for selecting optimal trading strategies, measuring their profitability, determining strategy parameters, identifying the best timing for order placement, and quantifying HFT activity (Kearns et al. 2010, Anane and Abergel 2014, Beckhardt et al. 2016). However, there remains to be more information regarding the optimal configuration of high-frequency strategies, specifically how they should be applied and which methods are suitable based on the trading algorithm.

When previous research was examined, it was discovered that there is a significant need for testing trading algorithms to avoid market crashes. Numerous papers present their findings in testing intraday or another low-frequency algorithmic trading (AT). However, HFT testing is a less researched field in cryptocurrency trading. As a result, in this paper, we implement a high-frequency trading testing method in the context of cryptocurrencies. Furthermore, the testing method is applied to pair trading strategies, which account for most AT strategies. (Fil M., 2020, Sarmento, S.M. and Horta, N. 2020, Chen C-H et al. 2022, Ungever C. 2015)

The market capitalization of one of the most popular cryptocurrencies, bitcoin, surpassed $300 billion in 2017. (Fischer, Krauss, & Deinert, 2019). According to the most recent data, the total market capitalization of all cryptocurrencies exceeds $609 billion (Best, 2021). Cryptocurrencies are a financial technology product gaining popularity but still need to be studied (Vo & Yost-Bremm, 2018). Previous studies have used cryptocurrencies in algorithmic pair trading. (Furlan, 2018) studied daily closing prices of cryptocurrencies using a pairs trading strategy and algorithmic trading. (Bai & Robinson, 2019) used cryptocurrencies, an arbitrage strategy between different trading systems, and daily closing prices. (Păuna, 2018) used a cryptocurrency arbitrage strategy on minute cryptocurrency data. What previous studies lack is the application of cryptocurrencies to the HFT environment. Another critical aspect is the formalized high-frequency trading algorithm testing method requirement. Because cryptocurrencies are characterized by price volatility and are not regulated by a central bank, their movement is more difficult to predict (Păuna, 2018).

Figure 1 demonstrates how the COVID-19 pandemic did not spare Bitcoin in 2020 and that when the markets plummeted in March 2020, the Bitcoin market crashed much more severely. Bitcoin's value halved in two days. Bitcoin surpassed an astounding $64,000 per coin in 2021, making headlines in the investment community. In a week, the global crypto market instantly lost $1 trillion in value. First, Elon Musk reneged on his pledge to accept Bitcoin as payment for Tesla vehicles. Then, China launched a further crackdown on cryptocurrencies. The public finally learned about the environmental effects of Bitcoin mining, and crypto investors found themselves in a familiar position: at the mercy of forces beyond their control. The occurrences mentioned above justify evaluating HFT algorithms to ensure that they do not exacerbate the problem and that investors in these methods do not lose money.

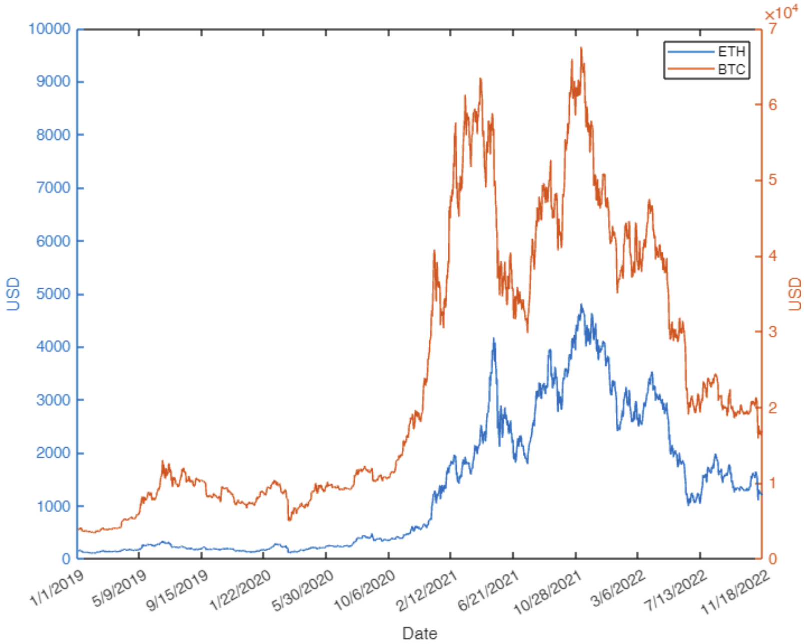

Fig. 1. BTC and ETH historical price data

This paper presents a methodology for testing HFT strategies on a graphics processing unit (GPU). The chosen research methodology is motivated by the need for efficient and rapid processing of high-frequency data in order to make timely buy/sell decisions in volatile market conditions.

The implemented testing method leverages kernel parallelization, code vectorization, and multidimensional matrices to distribute and parallelize calculations across CUDA cores, significantly improving the speed of HFT decision-making. This approach allows for the simultaneous execution of multiple calculations, enabling real-time analysis and swift response to market fluctuations. By adopting this methodology, we address the critical challenge of processing vast amounts of high-frequency data and executing complex calculations within strict time constraints.

To demonstrate the efficacy of the testing method, we apply it to various algorithmic trading strategies on cryptocurrencies during the volatile market conditions of the COVID-19 pandemic. The obtained results indicate the profitability and high efficiency of the testing procedure, as evidenced by the Sharp and Sortino ratios.

The subsequent sections of the paper are organized as follows: Section 2 provides a comprehensive overview of high-frequency trading, setting the context for the proposed methodology. Section 3 introduces the methodology details, outlining the steps involved in the testing process. In Section 4, we describe the datasets used for evaluation, along with the experimental settings, and present the results obtained during the experiments.

2. HIGH-FREQUENCY TRADING

High-frequency trading is the increasingly popular practice of executing trades based on split-second changes in market conditions using algorithmic programs. The majority of high-frequency traders are so-called market makers. Market makers are in high demand for low-liquidity markets, where they use algorithms to balance supply and demand. In these markets, market makers frequently pay low or no commissions (Herlemont, 2013; Zubulake and Lee, 2011; Jaramillo, 2016). The academic community in economics and finance regards HFT as beneficial to the market because it provides liquidity and thus facilitates the flow of commerce in capital markets (Jaramillo, 2016). Given that high-frequency trading must be done in milliseconds or even nanoseconds, all trading must be done using a supercomputer, which allows trades to be executed as quickly as possible. The HFT algorithm is best explained as follows:

1. Decision-making, trading, and other computer algorithms that enable electronic market trading without human intervention;
2. Low-latency technology like co-location servers speeds up and reduces transaction response time;
3. High-speed electronic market links;
4. High message rates (orders, quotes or cancellations).

High-frequency traders employ trading methods that seek opportunities to profit from short-lived trading in markets that would be impossible to detect or identify without the high-speed processing capacity of computers. These trading opportunities arise due to highly minor pricing anomalies in financial instruments, resulting in a modest profit per trade. However, high frequency generates more profit since large volumes can be traded. Thus, profit can be created from these minor price adjustments.

Pairs trading will be included in this research because it is one of the most popular strategies in algorithmic and high-frequency trading environments. (Fil M., 2020, Sarmento, S.M. and Horta, N. 2020, Chen C-H et al., 2022)

Pairs trading seeks to identify two financial instruments with similar characteristics whose equity securities are currently trading at a price relationship outside their historical trading range. This investment strategy involves purchasing the undervalued security while selling the overvalued security while remaining market neutral. It is also known as market neutral or statistical arbitrage.

3. HFT TESTING METHOD

This paper introduces a novel research methodology for testing HFT strategies on a GPU. The methodology stands out due to its efficient parallelization of calculations across CUDA cores, utilization of multidimensional matrices, and code vectorization, enabling faster HFT decision-making than traditional approaches.

One key aspect that sets this methodology offers distinct advantages over existing approaches (Zhang X . et al., 2023, Shi Z. et al., 2022, Xinhui T. et al., 2015) regarding speed, accuracy, and real-time decision-making. Furthermore, leveraging the GPU's computational capabilities ensures that the algorithm works with the most recent market information, which is crucial for HFT strategies' success.

Additionally, the proposed testing method addresses the challenges of high-frequency statistical arbitrage trading strategies by providing a comprehensive backtesting framework. Exposing the strategies to a stream of historical high-frequency cryptocurrency data generates a set of trading signals that capture the algorithm's performance, including profit/loss outcomes and the speed of signal detection and transmission.

The primary objective of the implemented testing method is to receive high-frequency data from an electronic market and send it from the CPU memory to the GPU global memory, where calculations are parallelized and processed, and buy/sell decisions are made. The data is then transmitted back to an electronic exchange. Data obtained from an electronic market and stored in the CPU memory is immediately sent to the GPU global memory, where the trading algorithm or algorithms are invoked. Backtesting of high-frequency statistical arbitrage trading strategies is introduced using the proposed method (Figure 2). Backtesting is carried out in this paper by exposing the high-frequency pair trading strategies to a stream of historical high-frequency cryptocurrency data, which results in a set of trading signals. Each trade has a profit or loss, showing how quickly the trading signal was detected and transmitted to an electronic exchange. (Vaitonis M., Masteika S. 2021)

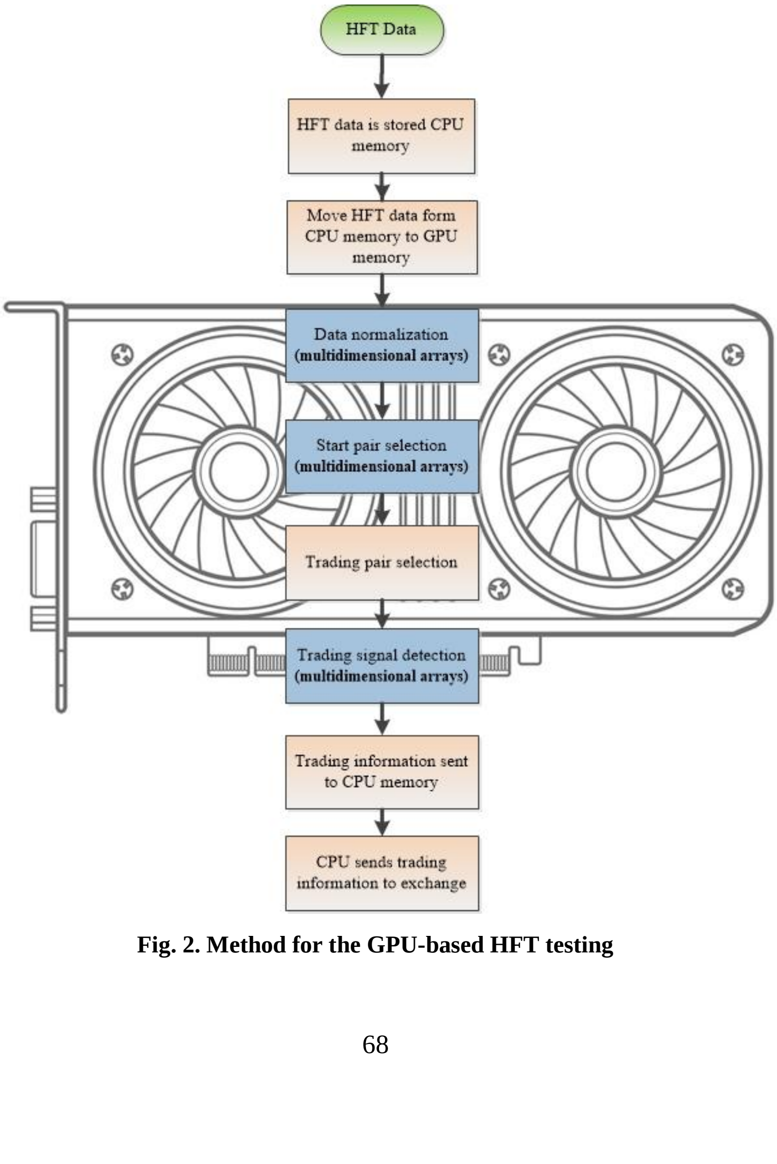

Fig. 2. Method for the GPU-based HFT testing

All possible calculations must be parallelized after splitting the data using multidimensional matrices to achieve faster trading decisions. Code vectorization was implemented using kernel parallelization to better use GPU cores and memory. Transferring the statistical arbitrage HFT algorithm to the GPU transforms the algorithm data into multidimensional matrices, and the algorithm calculations are performed in parallel by splitting them between separate parallel kernels, resulting in faster HFT decisions. (Vaitonis M., Masteika S. 2021)

HFT GPU trading testing method aims to parallelize all possible calculations across CUDA cores at the expense of GPU global memory. As demonstrated in Figure 3, the GPU components can be parallelized by implementing a multidimensional matrix. The algorithm allows the following functions to be parallelized:

1. Data normalization;
2. Selection of pairs for the trading period;
3. Seeking trading indicators;
4. Initiating transactions and closing positions based on the data supplied.

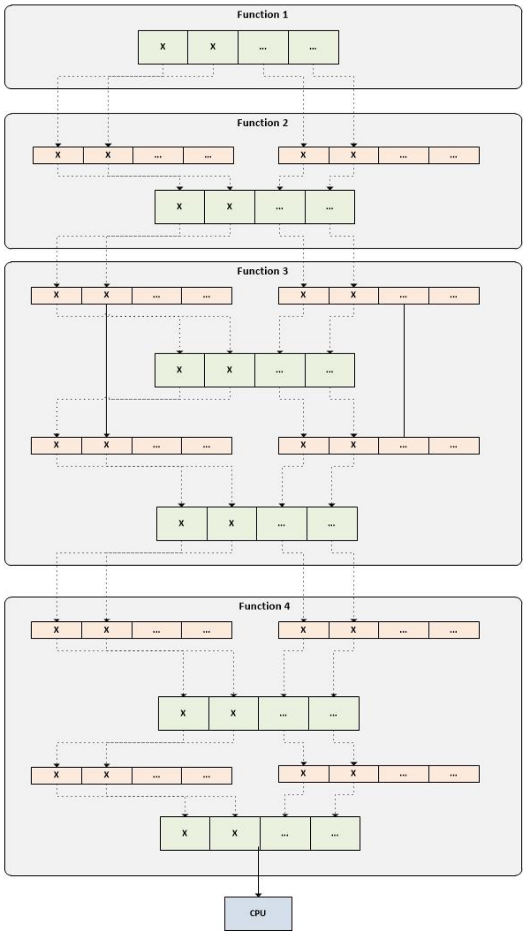

Fig 3. Parallelization of HFT Kernels within the GPU Environment

The high-frequency data stream from electronic exchanges is transformed into multidimensional matrices and distributed to the shared thread block memory after being transferred to the GPU global memory (Figure 3). Then, data can be normalized concurrently. The data that have been normalized are represented as multidimensional matrices. Finally, they are returned to global memory and relocated to the shared memory of the thread blocks. At this point, two trading pair selections can be parallelized as kernels running concurrently. Returning the data to global memory removes any duplicates from the trading pair. The trading decisions are then detected by the pair trading strategies that have been implemented. Positions are closed/opened in parallel at the end, and positions held for too long are closed. (Vaitonis M., Masteika S. 2021)

As shown in Figure 3, the objective of the trading algorithm on the GPU is to parallelize all possible calculations across the CUDA cores at the expense of the GPU global memory.

Data is received from an electronic exchange at the start of the HFT testing, and the CPU prepares the data before it is transferred to the GPU. The data transfer uses the algorithm's "Function 1" function, which starts on GPUs and creates GPU variables. After that, the "Function 2" function is invoked to parallelize the calculations and transfer the entire trading algorithm to the GPU. Calculations must be performed inside the GPU to be faster. Each CPU CUDA kernel cycle includes calculations. Calculations are not queued but are performed concurrently. The "Function 2" function creates the first three-dimensional matrix, which forms a matrix with prices indicating purchase and sale prices. The formation of this matrix activates the "Function 3" function, which aids in the parallelization of trading pair selection, trading signal detection, and closing trade signals. The following three-dimensional matrix was created for all possible cryptocurrency pairs. Simultaneously, the search for possible trading pairs is carried out. When the pair selection function is invoked, a new three-dimensional matrix is created that contains only the selected pairs. At the same time, the algorithm eliminates trading pair duplicates. The "Function 4" function is then launched, which detects trading signals on all trading strategies that have been implemented. The obtained results are saved in a three-dimensional matrix. Existing positions are checked in parallel to see if a closing signal has occurred or if the maximum time to keep the positions open has already been reached. The trading algorithm concludes when it sends the generated orders to the CPU, which sends trading or cancellation orders to electronic exchanges based on the information received. (Vaitonis M., Masteika S. 2021)

The presented HFT testing method offers a novel and valuable contribution to the field of HFT testing. By harnessing the computational capabilities of GPUs, parallelizing calculations, and utilizing multidimensional matrices, our approach enhances the efficiency, speed, and accuracy of HFT decision-making. Furthermore, it provides researchers and practitioners with a robust framework for evaluating the performance and profitability of HFT strategies, paving the way for further advancements in the field.

4. EXPERIMENTS AND RESULTS

The experiments in this study aimed to evaluate the effectiveness of the HFT testing approach based on kernel parallelization, code vectorization, and multidimensional matrices on GPU. The testing approach was applied to various algorithmic trading methods on cryptocurrencies in volatile market conditions during the COVID-19 pandemic.

The experiment involved simulating trades using the selected algorithmic trading methods and evaluating their performance under the proposed HFT testing approach. The performance was measured in terms of the Sharp ratio and Sortino ratio to determine the efficiency of the algorithmic trading methods.

Multiple trials were conducted to ensure the validity of the results, and the average results were recorded and analyzed. Additionally, the experiment was compared with market results to verify its consistency with real-world trading scenarios.

The results of the experiments provided valuable insights into the effectiveness of the proposed HFT testing approach, enabling the researchers to conclude that it is effective for evaluating HFT strategies in the most volatile cryptocurrency markets.

4.1. Dataset

The dataset used in this study consisted of cryptocurrency data obtained from two major exchanges, Bitstamp and BitMEX, from 01-12-2020 to 31-01-2021 during COVID-19. The research specifically focused on Bitcoin (BTC, XBT) and Ethereum (ETH) as the chosen cryptocurrencies. This period was selected for several reasons, including its relevance to understanding the impact of the pandemic on cryptocurrency markets and the availability of comprehensive tick-by-tick order book data from two independent cryptocurrency exchanges.

We analyzed data during the COVID-19 pandemic to capture the heightened volatility and market conditions. During this period, several highlights regarding COVID-19 could affect electronic markets. These include new variant detection, the surge in cases and increased strain on healthcare systems, new lockdowns, and travel restrictions (Wibmer C.K. et al., 2021; Islam N. et al., 2021, Saha M., 2021).

These two exchanges were chosen due to their reputation as reliable and established players in the cryptocurrency market and their large volumes of daily trading activity. Using Bitstamp and BitMEX allowed us to gather comprehensive and reliable data for this research. Furthermore, the 24/7 trading availability of these exchanges enabled continuous data collection, ensuring a comprehensive representation of market dynamics.

The data collected from these sources included historical pricing information and trading volume for various cryptocurrencies. This data was used to simulate the performance of algorithmic trading strategies under different market conditions and to evaluate the effectiveness of the HFT testing approach developed in this study.

In order to ensure the accuracy of the results, the dataset was thoroughly pre-processed and filtered to remove any irrelevant or inconsistent information. This included removing data generated from abnormal market conditions, such as sudden spikes or dips in pricing, and correcting for discrepancies between the sources used.

This dataset allowed for a thorough evaluation of the HFT testing approach and its ability to accurately reflect the performance of algorithmic trading strategies in real-world conditions.

4.2. Data normalization

Because of the volume of transactions that occur in such short periods, HFT is recognized as a subset of financial markets and an essential topic in data science (Han H. et al., 2020). HFT data is distinguished by many observations (transactions) but few variables. Working with high-frequency data is no longer possible in time because it is not possible for a transaction to occur every nanosecond with high frequency, for example, nanosecond data, so some periods with nanosecond accuracy do not exist. This necessitates data preparation and processing. In their paper, H. Han, J. Teng, J. Xia, Y. Wang, Z. Guo, and D. Li (2020) mention that a daily data set is being created, in which data is provided at a frequency of one minute, and additional variables such as change time (the ratio of stock price change per minute), the volume of trades (frequency of trades per minute) are included. Sh. Chen et al. (2018) discuss data normalization, which occurs when raw data values are transformed into new values within the [0, 1] interval. This step is used to reduce model errors. According to P. Treleaven et al. (2013), the need to unify the trading periods of the investigated financial instruments is critical; if any financial instruments were not traded for the entire duration of the investigation, they should be excluded from the scope of the investigation. In a paper by Liu G. (2019), it is stated that tick-by-tick data may not have price values for every second because the research is carried out with the precision of seconds. Because tick-by-tick data includes a record of all market trades, some seconds may have had no trades and thus do not exist in the data set. The author's work discusses how we cannot use such data in research and how to fill in the blank entries in the time series.

The fundamental issue with high-frequency data is the discrepancy between the timestamps of the associated cryptocurrencies. It has been observed that the timestamps for trades or bid/ask changes occurring within the same trading second differ. Therefore, the timestamp sequences of the associated cryptocurrency must be compared. If the timestamps differ, the cryptocurrency with the missing timestamp is filled in using the previous bid/ask or trade prices. As a result, the timestamps of the related cryptocurrencies are combined, and the prices are maintained up to date.

Data is another part that requires processing. For example, pair trading requires comparing the prices of various financial instruments. However, different financial instruments have values in significantly different ranges, which is why there is a need to normalize their prices. Therefore, the normalization of high-frequency data is essential for recalculating the prices of the related financial instrument to a specific unit, reducing the noise of price changes and allowing for a more qualitative comparison. In this study, for data normalization we are using the following equation (Vaitonis, Masteika, 2018; Perlin, 2009):

$$P_{i,t} = \frac{p_{i,t} - \mu_{i,t}}{\sigma_{i,t}} \tag{1}$$

where $P_{i,t}$ is the normalized price of cryptocurrency price i at time t, $p_{i,t}$ – cryptocurrency price, $\mu_{i,t}$ – the empirical mean, $\sigma_{i,t}$ – standard deviation.

Following normalization, the following stage is to look for all cryptocurrency pairs that could be used for trading signal detection. Only normalized cryptocurrency prices are used in this step, and all calculations are performed on the GPU. Finally, the pair is chosen following the trading strategy. It was initially stated that there are three different approaches to it:

1. Distance method.
2. Stochastic Spread Method.
3. Cointegration method.

The trading signal search is initiated once all possible trading pairs have been identified. The data is then reviewed to verify if the same trade signal has yet to be issued or has already been closed and could be reopened. When a trading signal is detected, data from the GPU memory is transferred to the CPU memory and ultimately to an electronic exchange. Finally, the finalized trading outcome for the given day is calculated after all trade decisions have been completed.

4.3. Efficiency measure

Profitability from each trading day will be calculated and summed to determine efficiency. However, more than evaluating the total daily gains obtained from a trading strategy alone is required to determine the trading strategy's efficacy. When assessing the effectiveness of a trading strategy, it is also necessary to consider the risk and loss trades. Efficiency measurement methodologies differ based on the algorithm used. How an algorithm functions in a high-frequency environment differs drastically from that in a low-frequency environment. For intraday trading, the profit factor proposed by Z. Huang and Martin (2019) can be calculated as a profit/loss ratio using the following formula:

$$P = \frac{p_a}{l_a} \tag{2}$$

where P is the calculated profit factor, p_a – profit derived from trading strategy and l_a – loss derived from trading strategy. However, this strategy would only be effective in a high-frequency environment due to the weight of minor transactions and their daily value. Another way to measure algorithmic trading effectiveness is the success rate (Wu et al., 2017, Krause & Fairbank, 2020). The formula is straightforward. To calculate it, subtract all profitable trades from all unprofitable trades. This measure would also be ineffective in a high-frequency environment due to the large number of deals each day and the importance each of these trades may have on overall trading performance. Sharp and Sortino ratios will be calculated to assess HFT algorithmic techniques. The two indicators were beneficial for assessing this type of trading strategy. (Kumiega A., Neururer T. and Van Vliet B., 2014; Zhang Z., Zohren S. and Roberts S., 2020; Stübinger, J., & Bredthauer, J. 2017)

Sharp ration is calculated using the equation:

$$Sh = \frac{\mu_a}{\sigma_a} \tag{3}$$

where Sh is Sharp ration, μ_a – all trades profit/loss mean and σ_a – standard deviation.
Sortino ration for this experiment will be calculated using the equation:

$$Sor = \frac{A_r - R_r}{D_d} \tag{4}$$

where Sor is Sortino ration, A_r – average realized return, D_d – target downside deviation and R_r required rate of return.

In our case, the required rate return will be 25.5%, as this is the calculated average daily return for algorithmic trading strategies (Baron M. et al. 2017).

4.4. Results

The analysis relied on tick-by-tick order book information from two independent cryptocurrency exchanges, Bitstamp and BitMEX. Every incremental update or "delta" to the order book, as it occurs in real time, constitutes information in data utilized. Furthermore, each new, updated, or removed bid, ask, price level, quantity, and corresponding timestamp or sequence ID. The data is for Bitcoin (BTC, XBT) and Ethereum (ETH) from 01-12-2020 to 31-01-2021 during COVID-19. Pairs can be identified by searching for the corresponding cryptocurrency in the same exchange and searching for the same cryptocurrency in different exchanges. Bitstamp and BitMEX exchanges were utilized to obtain Bitcoin information. The sample tick-by-tick data used is shown below (Table 1).

Tab. 1. Data sample used in this research

Time stamp	Price	Trade amount
1606798799968	19369.52	0.14751233
1606798800286	19368.71	0.2581
1606798800695	19383.09	0.16267634
1606798801076	19366.99	0.1
1606798801534	19371.35	0.258
1606798801904	19364.62	0.1
1606798802318	19377.63	0.20545567
1606798802745	19375.80	0.74168653
1606798803079	19368.70	0.2577
1606798803519	19366.36	0.14746576
1606798803886	19371.74	0.77962337
1606798804624	19367.32	0.38889417
1606798805031	19368.55	2
1606798805358	19367.89	0.21
1606798805781	19368.45	0.2576
1606798806105	19367.86	0.233
1606798806507	19374.22	0.1

The data shown in the table consists of three variables: time stamp, buying/selling price, and trade amount. The trading algorithms used in this paper do not consider trade amounts. As a result, this variable was eliminated, and just the time stamp and cryptocurrency price for that trade were considered. The average response time for all three cryptocurrencies is 0.093 seconds. This is the rate at which new information is received by the high-frequency trading algorithm used in this study. The average rate at which new information about cryptocurrency prices arrives serves as a baseline for the trading algorithm while making trading decisions. The mentioned speed is only average, implying that trading decisions made by the algorithm must be significantly faster. High-frequency trading algorithms must ensure that they work with the most recent information, which is why they must be able to assess the most recent information. Furthermore, once a trading decision is made, it must be communicated to the market, which takes time. This time must also be taken into account. Based on these requirements, the high-frequency trading algorithm testing technique was developed, which should aid in measuring not only the algorithm's efficiency and profitability but also the trading speed and accuracy.

When comparing cryptocurrencies, the average number of time stamps per trading day after data normalization and filling missing timestamps was 5539536. It is worth noting that due to the way these two exchanges (Bitstamp and BitMEX) operate, it is possible to trade 24 hours a day, 365 days a year.

The HFT algorithm strategy testing method offered should be implemented on GPU. To meet the high-frequency trading requirements, it was implemented on Nvidia GeForce RTX 2080 Ti using parallel calculating methods. Each day's trading return was determined after all cryptocurrency data was passed through the provided algorithm. Furthermore, the finalized algorithm result will be derived using the previously specified efficacy measurement methodologies.

The program divided each trading day result from 01-12-2020 to 31-01-2021. The sample results for four separate trading days are represented in the Table 2.

Tab. 2. HFT strategies daily performance sample showcasing long/short position and total return

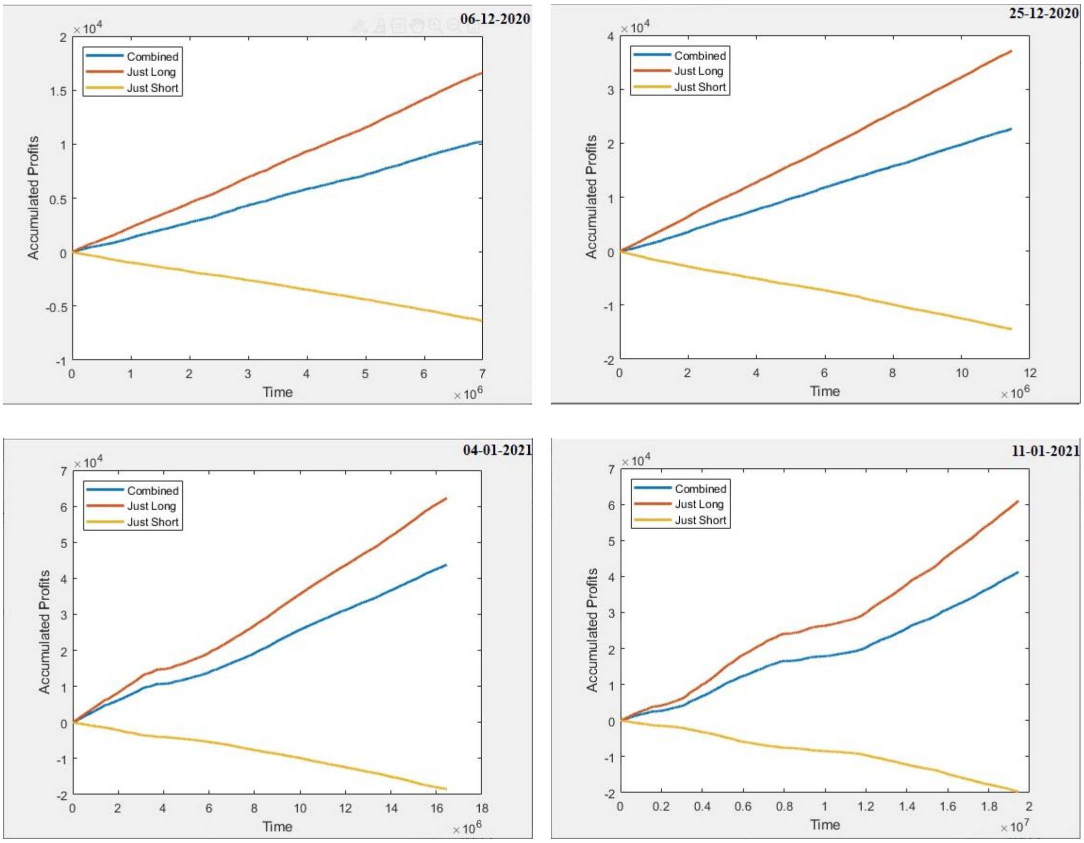

Figure 4 below depicts the overall return performance of tested HFT trading strategies on cryptocurrency. It displays the return for each trading day. Even if there are several surges and drops, each of the days performed with a positive return.

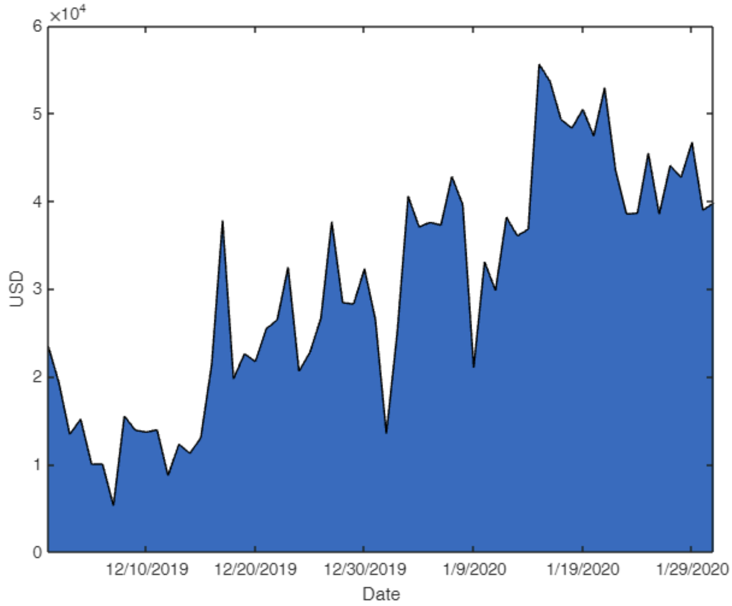

Fig. 4. HFT daily returns

The total profit for the entire trading period was determined to be 1872670.38 USD. It is worth noting that no commissions were considered when calculating the end-of-day result, and the initial investment amount was USD 100,000. Therefore, the final profit throughout the two-month trading period mid-COVID-19 was 18 times greater than the capital used at the start. Commissions may be relevant depending on the exchange or broker used, affecting the total profitability of the HFT algorithmic trading strategy. However, commissions for HFT are reduced, fixed per number of trades, or even non-existent to provide liquidity for the exchange.

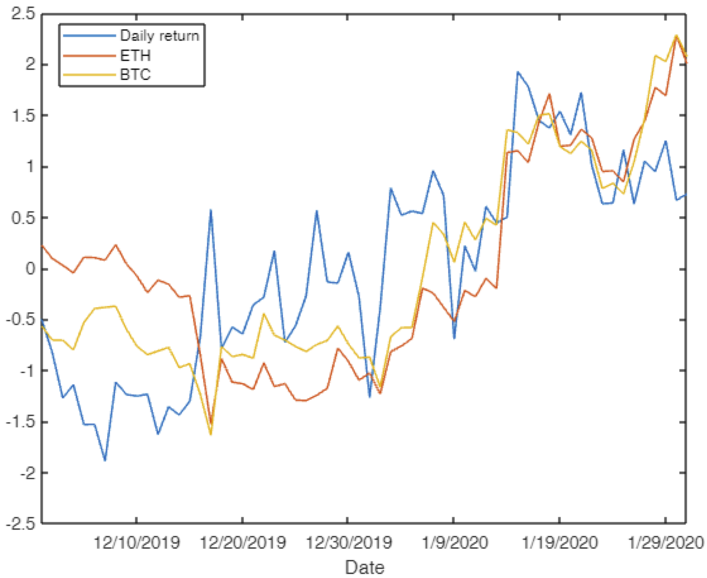

Fig. 5. Overall HFT return compared to ETH and BTC daily prices

Therefore, the overall profit for the trading period needs to demonstrate the effectiveness of the trading algorithm or how well it performed. As a result, we examined ETH and BTC time series for daily prices (Fig. 5). We needed to normalize prices to examine the movement of these two cryptocurrencies compared to delivering profit with a testing trading algorithm. Figure 5 below shows the performance of the tested trading algorithm utilized in this study in greater detail.

When data is normalized, observing patterns and seeing that the daily tested HFT algorithm return follows the price of ETH and BTC is feasible. However, when cryptocurrencies experience specific disruptions, the tested algorithm performs well. This is noticeable when cryptocurrency values rapidly rise or fall. It demonstrates that the trading algorithm performs well in volatile environments. Furthermore, these findings show that tested trading strategies can overcome market volatility without causing investors to lose money. On the contrary, these tactics will perform best during these unpredictable periods in the middle of COVID-19.

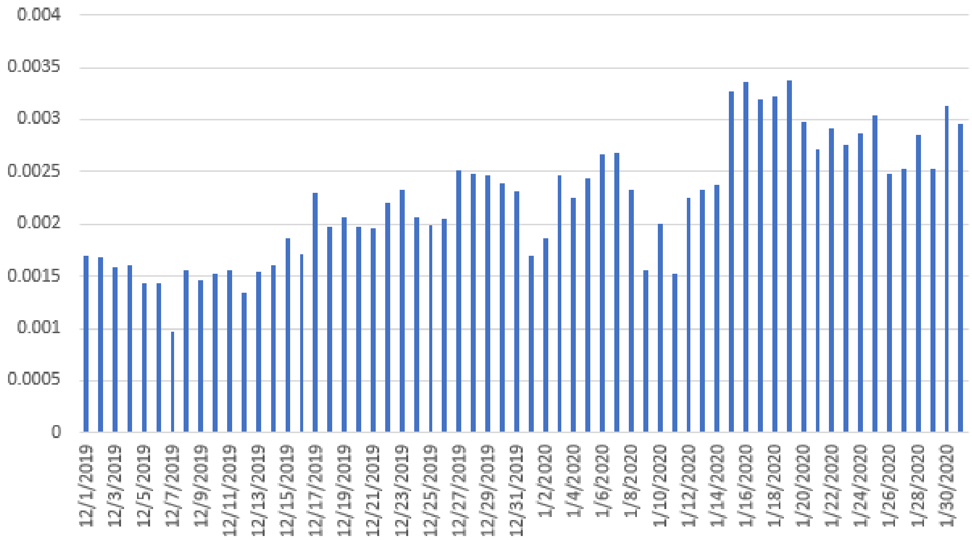

Fig. 6. Average return per trade

It should not be surprising that a more significant number of trades each day resulted in a greater daily return. Even though the average return per trade is relatively tiny (Fig. 6), averaging 0.00223 cents each, the aggregate daily return is highly important because HFT results in hundreds of thousands of trades daily.

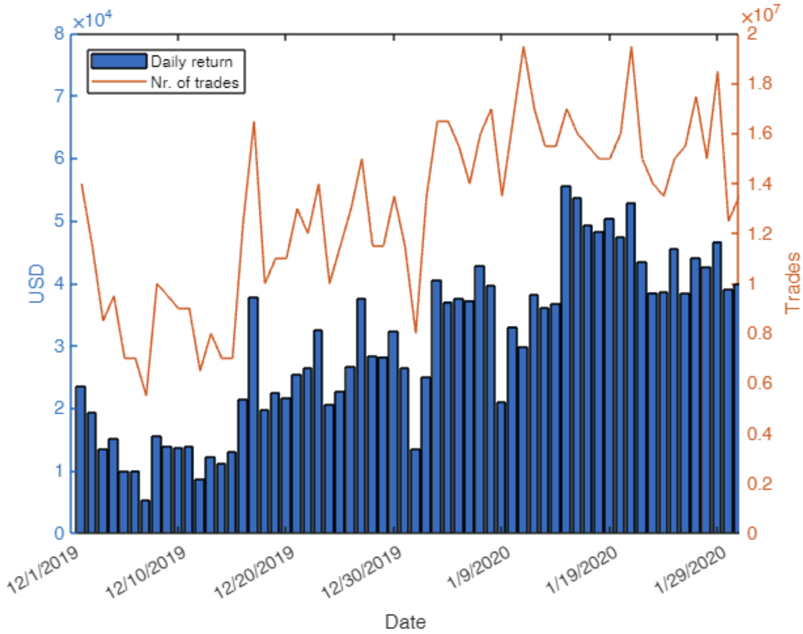

Fig. 7. Number of trades compared to daily return

The accompanying chart (Fig. 7) depicts the total number of daily trades and the returns generated by HFT strategies applied to this research HFT testing method. This graphic illustrates the overall performance of tested trading strategies and demonstrates that the test method applied served its intended goal. In addition, HFT strategies tested under volatile market conditions demonstrated effective performance. It was calculated using the Sharp and Sortino ratio. First, the Sharp ratio for the entire trading period from 01 December 2020 to 31 January 2021 was determined to be 2.29, while the Sortino ratio was 2.88. Thus, the testing procedure was verified considering the overall profitability of the tested algorithmic trading strategies, two ratios, and the trading speed attainable at 0.00000107. Second, HFT strategies' resilience to market shocks, in this case, COVID-19, was demonstrated.

5. CONCLUSION

In this study, a novel HFT strategy testing approach based on kernel parallelization, code vectorization, and multidimensional matrices was constructed on GPU. During COVID-19, the chosen testing approach was applied to various algorithmic cryptocurrency trading methods in volatile market conditions. The experiment showed that the method is ineffective when applied to diverse hardware. The results demonstrated that evaluating HFT strategies effectively test them on the most volatile cryptocurrency market.

The experiment results revealed that the chosen testing approach was particularly effective when applied to the most volatile cryptocurrency market. Furthermore, the measured Sharp ratio of 2.29 and Sortino ratio of 2.88 demonstrated the efficiency and profitability of the HFT strategies tested using this method.

While the proprietary and competitive nature of HFT strategies may limit the availability of specific data sets and restrict the dissemination of proprietary algorithms, developing a novel HFT testing method presented in this paper offers significant advantages in speed, accuracy, and real-time decision-making. By leveraging the computational power of GPUs and employing efficient parallelization techniques, this methodology enables faster HFT decision-making compared to traditional approaches. Furthermore, the comprehensive backtesting framework addresses the challenges of high-frequency statistical arbitrage trading strategies by generating trading signals based on historical high-frequency cryptocurrency data, capturing the algorithm's performance and signal detection, and transmission speed. These advancements contribute to improving trading strategies and hold potential for applications in other scientific domains that deal with large-scale data analysis and rapid decision-making.

Further study on high-frequency trading testing methods might be conducted using a developed tool that would link directly to electronic marketplaces. This will enable real-time receipt of high-frequency trading data and simulation of trade decisions, resulting in finalized thresholds for measuring different trading strategies in this context.

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