High-Frequency Trading in Stock Market

Mayank Gupta[1]

[1] *Jaypee Institute of Information Technology, mayankgupta0519@gmail.com*

Abstract - *Since its innovation, high-frequency trading has portrayed a significant role in the development of different financial markets across the globe. Artificial intelligence has opened new roads for researchers to enhance the performance of sophisticated decision-making by computers. This paper examines the high-frequency trading working and widely used strategies, as the role of artificial intelligence in shaping the future of HFT by surveying 24 already existing research articles. It also focuses on the impact caused by HFT in different aspects and the regulations around it.*

***Key Words*: High-Frequency Trading, Stock Market, Machine Learning, Neural Networks, Impact, and Regulation**

1. INTRODUCTION

High-Frequency Trading (HFT), a type of algorithmic trading, is defined as a method in which a very large number of orders are transacted within a fraction of a second. This is done through different complex algorithm-based programs. In general, algorithmic trading saw its rise when the minimum tick size was changed in the US market, electronic communication networks and electronic execution of orders were introduced, and when SEC passed the Regulation Alternative Trading Systems and Regulation National Market System. The emergence of artificial intelligence and improvement in the speed of processing data are the reasons for HFT's origin in the financial markets. Artificial intelligence made our computer programs capable of performing tasks that require human intelligence and faster processing speed reduced the time taken by machines to execute and provide results. Despite being a recent innovation, HFT has influenced the related markets in multiple aspects and therefore has been under scrutiny from multiple organizations and governments.

2. DEFINITION

The main objective of this paper was to study the relationship between HFT and artificial intelligence. Initially, HFT and the corresponding different strategies are examined in terms of the factors it is based upon. Then, the role played by artificial intelligence is scrutinized, as to how it will shape HFT's future. Lastly, the impact of HFT in different financial markets is observed and the regulations implemented and proposed so far for proper acceptance of HFT.

3. DISCUSSION

The discussion is bifurcated into three sections. The factors behind the HFT working and different strategies are discussed in 1st section. 2nd section presents the role of artificial intelligence in HFT. Lastly, in the 3rd section, HFT impacts in different financial markets are observed and the policies and regulations put forward by different government bodies are also discussed.

3.1 HFT Working and Strategies

As per the studies conducted in [2,5,6,9], it is established that speed and latency introduced while transferring information and processing commands are used to a good advantage in successful HFT. Latency is defined as the lag between when an order is sent to an exchange and when it is processed and executed. It is observed that it has decreased from 0.6 to 0.00113 (sec2) within the last two decades because of the exponential increase in the computation power of computers. For several years, many trading firms have been trying to achieve the lowest possible latency on their systems, to receive and process information as quickly as, if not faster than, their competitors. Latency arbitrage is known as the technique in trading where the orders are transacted utilizing the minor price differences caused by acquiring the subsequent data from exchanges slightly ahead of other investors. To generate profits from latency arbitrage, the user must get the prices slightly ahead of other market participants. Therefore, many different technological breakthroughs and strategies are utilized to achieve the lowest latency. Fiber optics are utilized to reduce transmission time as well as to push large amounts of data across the network with high transfer speeds. Fast Processing Gate Arrays (FPGA) are used to perform repeated and rapid functions from the implemented algorithms and multi-core processors are employed for faster data processing. Also, many firms achieve low latency by locating their servers as near to the exchanges as possible to get raw, unfiltered feed. The reduced physical distance between the trading server and exchanges guarantees low latency. In contrast, most other market participants utilize one single channel encapsulating the best prices and other corresponding data from all the exchanges, ECNs, and Alternative Trading Systems (ATS). The process of combining into one channel introduces some latency, and the data is already slightly old by the time it reaches them.

As HFT is a type of algorithmic trading, therefore all the trading decisions are taken by the implemented algorithms in the computer program. In [9], the author implemented a genetic programming and simulation-based computation model to address the trade-off between the speed and sophistication of algorithms. The algorithms are designed to implement the mentioned different strategies to book profits.

1) *Market Making:* In this technique, the profit is booked on the bid-ask spreads. The algorithm bet for both sides of the trade by putting a limit order to sell slightly above or purchase slightly below the current market price, and therefore benefiting from the difference between the two. The system can enter trades automatically when certain conditions are met as per the algorithm.

2) *Liquidity Rebate*: Multiple exchanges and ECNs employ the 'maker-taker model' through which they provide a rebate for providing liquidity in the market. The HFT programs look for large orders and provide a share of liquidity for them. Then these shares are offered back to the market by placing a limit order. Through this, some profit is generated through accumulating rebate fees for providing liquidity.

3) *Statistical Arbitrage*: Profits are reaped from market arbitrage by taking advantage of the variability in characteristics such as rates, prices, and other conditions that exist between different exchanges or asset classes. Traders also take advantage of the difference between co-related securities like derivatives, Exchange Traded Funds (ETFs), and other fundamental securities and equities.

4) *Momentum Ignition*: This strategy comprises starting and canceling a series of transactions and orders for a particular asset in a specific direction, intending to ignite a quick market price movement. The rapid submission and cancellation of these orders may be recognized by other traders' algorithms, resulting in them buying or selling the asset. Because the firm submitting these orders and trades has already built a position, it can profit by leveraging the ensuing price movement. As it raises multiple questions on the ethical ground, it has been identified as a prohibited market manipulation from ESMA, ICE Canada as well as from CME Group.

5) *Employing Co-location Services:* To have an upper hand over other market participants, multiple firms place their servers as near to the exchange as possible to reduce the distance for transmission of the data feeds from the exchanges. This is achieved by utilizing co-location services and sometimes exploiting the relationships with some exchanges.

6) *Quote-stuffing:* In this strategy, an unusually large number of orders are submitted, which are then immediately canceled. As a result, it causes order congestion. Its goal is to slow down the exchange's operations and lower the entry barrier for other traders. A high volume of order submissions may also cause the exchange receiving the quotations to lag behind other exchanges, providing arbitrage opportunities for the manipulator. Other investors may be misled about which exchange has the most liquidity or the best pricing. Canceling orders in large quantities in a short time monopolizes resources. Other non-HF investors are slowed by the trading profit made through such manipulation.

3.2 Role of Artificial Intelligence

Recently in the past few years, it can be observed artificial intelligence has increased profits by designing better algorithms and frameworks for improved decision-making by HFT programs. In financial markets, an increasing number of academics use AI techniques such as machine learning and neural networks. Some of the studies done to present the frameworks are analyzed briefly.

In [20], an analytical framework for HFT based on order book information was proposed. In the designed algorithm, an optimizer based on Volume-Synchronised Probability of Informed Trading (VPIN) and Generalised Autoregressive Conditional Heteroscedasticity (GARCH) was used throughout the activation Support Vector Machine (SVM) layer. The effectiveness of the methodology was back-tested with observations of the CSI 300 futures which result in better results and returns as compared to other only GARCH and VPIN-based models.

In [15], to maximize the return on investment by forecasting the medium-short-term trend in FOREX an HFT algorithm was presented. The algorithm was derived from supervised deep learning and reinforcement learning algorithms. The framework consisted of an LSTM-based deep learning model, followed by an RL Correction block. A grid trading system was also implemented in the proposed strategy for HFT. The proposed framework reported an ROI of 98.23% and a market drawdown of 15.97%.

In another study [11], a deep reinforcement learning-based framework was introduced for active HFT which is trained on limited order book data for the NASDAQ platform. The model is trained with the Proximal Policy Optimisation algorithm and tuning of hyperparameters is done by the Sequential Model-Based Optimisation (SMBO) method.

A very similar study [13], proposed the use of Very-Long Short-Term Memory Networks (VLSTMs) to handle the long sequences in the data points in HFT. The proposed model was tested by predicting the mid-price movement from limit order book data for 10 days with almost 400,000 ticks with 144 features representing each tick. The VLSTM-based model reported the best F1 score as compared to other LSTM models.

A novel architecture based upon Spiking Neural Networks and unsupervised learning to predict the spikes in price time series instead of the movement directions was presented in [16]. The presented architecture was backtested on a dataset of the crude oil and gold futures for 23 days of May 2017 from Chicago Mercantile Exchange. Spike accuracy and Momentum spike percentage were used as the performance metric Spike based networks reported the best-accumulated return as compared to other movement and LSTM-based models.

The authors in [22], aimed to demonstrate a volatility-based study in HFT by using big data analytics. The proposed model was intended to estimate volatility in HFT by exploiting the seasoned volatility on a dataset from NYSE with the help of Spark to carry out big data analytics.

The work presented in [18], contributed an ensemble forecasting model of ARIMA-GARH-NN with LSTM for HFT and compared the technical indicators' impact on the forecasting values as the evaluation method for the proposed model. The model was trained on S&P 500 intraday dataset. The main concept was to test how near the model was to reality to determine the amount of risk that the user would take while guessing the values x minutes ahead. As a result, various trials were conducted to forecast 1-minute, 5-minute, and 10-minute ahead prices. Multiple technical indicator values are included as features for additional study, and RMSE is employed as the performance metric.

In [21], the authors presented architecture to examine the impact of AI learning and the trading speed of HFT in limit-order markets. They employed a genetic algorithm with a system classifier as their AI learning tool on the market conditions to learn from historical prices, quotes, fundamental value, bid-ask spread, and other market information. They also observed both High and Low-frequency traders to examine their interplay and impact. The findings showed that trading speed has an inverse U-shaped non-linear influence on order submission, profit, and information efficiency because of the trade-off between the information advantage effect and competition effect for HFT. This provides an incentive for HF traders to avoid trading too quickly, which may help to increase pricing efficiency while also giving meaningful knowledge for investors and regulators to supervise AI trading.

To improve the overall operational performance in HFT, some new CNN-based architecture applied to order-based features was proposed to predict the direction of mid-price trends [12]. They introduced an order-encoding method to convert the order book information into appropriate input variables for the neural network. An average convolutional neural network (A-CNN), a convolutional neural network (CNN) extension, was used to extract characteristics to forecast prices from the given order book information. In addition, an upgraded version of A-CNN (A-CNN+) was demonstrated to solve the issues associated with A-CNN. Experiments employing large-scale high-frequency trading data revealed that the proposed method outperforms other benchmark methods and that the learned model responds significantly to the ordering process in all tasks. Investment simulations were carried out to illustrate a practical application to buying and selling based on model predictions by the suggested method, and positive results were obtained. As a result, the model's applicability was suggested.

To provide tools to analyze the security and reliability of the widely used artificial intelligence models in HFT, a study was done to analyze the robustness of the models from the perspective of adversarial machine learning [17]. To do so, they implemented a linear classifier, a multi-layer perceptron (MLP), and an LSTM and developed a basic adversarial attack on these models. It was discovered that, while neural network models outperform classic linear valuation models in this situation, they are less robust. It was also discovered that the same adversarial patterns that deceived one model also deceived others and that these patterns are highly interpretable by humans. The portability of these attacks, combined with their potential to be effective with a low attack budget, suggests that they may be used by a malevolent actor with minimum knowledge.

3.3 HFT Impact and Regulations

High-Frequency Trading has indubitably changed the current financial setting by introducing a non-conventional method of trading. According to the most recent reports (2020), HFT contributes 50% of the trade volume in the US equities markets and around 24% to 43% in the European equity markets. Countries in the Asia-Pacific area, such as Japan and Singapore, have also welcomed HFT by enacting HFT-compliant regulations. Citadel LLC, Virtu Financial, IMC Financial Marketplaces, and Tower Research Capital are among the leading organizations involved in HFT across a wide range of financial asset classes and markets.

In a particular study [14], the present scenario and the scope of future developments in HFT were discussed for the Asia-Pacific region. They initially identified the different market regulatory factors for HFT and gathered information about the financial markets of Australia, China, Hong Kong, India, and Japan. Then they compared the empirical findings for the Asia-Pacific region with other regions in terms of liquidity, information and price discovery, volatility and system risk, quote flickering, profitability, and the effects of anticipatory HFT. They reported that it is necessary to determine the optimal market design so that it can focus on more microstructure effects. The limitations faced were in the form of vagueness in the source of computerized traders' private data and therefore focus on the implications of HFT.

HFT has impacted the current financial setting in many positive aspects. According to reports, the entrance of HFT has resulted in a rise in market liquidity due to an increase in the number of trades and thus portrays a very prominent role in supplying order flow and increasing liquidity level. Following the establishment of HFT, the bid-ask spreads shrank, resulting in more regular and accurate price updates. According to an NYSE Euronext analysis, quoted spreads from 2007 to 2009 were lower than those from 2002 to 2006, when HFT was less widespread, suggesting that HFT led traders to offer the most competitive bid-ask pricing. Because HFT ensures accurate pricing at shorter time intervals and reduced trading costs, market efficiency has grown because prices are now more precisely and swiftly displaying market information. It has also enabled narrower spreads and cheaper trading costs, for individual investors who invest in the markets indirectly through mutual and pension funds. As HFT has raised trading volumes on exchanges and ECNs, many exchanges and ECNs have reported an increase in revenue and transaction fees.

While HFT is being widely accepted and appreciated for its positive impact across the globe, it has been under scrutiny from multiple governments, and organizations for the risks it brings with itself. Some HFT tactics are speculated as they look for recurring patterns in trading and keep the institution ahead by detecting an incoming order flow, after which it buys the security and then sells it to the institution at a slightly higher price. As a result, institutional investors' strategy and market impact expenses may suffer. Sudden price changes and short-term volatility are often caused as HFT includes rapid intraday trading with positions often held for minutes or even seconds. As HFT volumes are typically a rather substantial proportion of total trading, price swings generated by this approach can contribute to overall market volatility. Furthermore, the practice of initiating deals and immediately canceling them to trigger automated buying from other corporations is an ethical issue that many experts have questioned. Usage of co-location facilities and raw data feeds, which are often unavailable to smaller firms and retail investors, put them in a disadvantageous position. Furthermore, certain HFT businesses frequently enter trades just for the liquidity rebate, which provides no value to the retail or long-term investor.

The negative impact of HFT came under the limelight during the "Flash Crash" on May 6, 2010. During these 36 minutes crashes, multiple US stock indices collapsed by a very significant value and rebounded rapidly. Over $1 trillion in equity was reported as a loss because of this flash crash. In [8], it is mentioned that many E-mini futures contracts of a total worth of $200 million were entered only to cancel later. These orders were replaced or modified for about 19,000 before cancellation and represented about 20% of the total orders. These orders were able to influence numerous genuine investors instantly. The DOW reported a drop of about 9% in the value within minutes and also recorded the largest intraday point drop. Surprisingly, the market recovered about 90% of the loss within 30 minutes. In another incident, Knight Capital Group was on the verge of the end when their trading software bought about 150 different stocks with a total worth of $7 billion without any financial support, on NYSE within the 1st hour of trading on August 1, 2012.

To avoid such negative impacts of HFT and to regulate them, multiple frameworks and policies have been introduced. Mifid2 and MAR are the two different regulations implemented by the EU for European markets to adapt and regulate the obstructive side of HFT and the firms employing it [10]. Some of the policies included in these regulations are mentioned below:

- Before accessing markets, all HFT firms must be authorized by the regulators according to Mifid 2, Article 2.
- To monitor the algorithms, compliance is imposed by Article 17 (investment firms) and Article 48 (trading venues). Responsibility for disruptive occurrences can now be assigned to all relevant people at all levels of the organization, from the developer to the trader, the trading supervisor, compliance, and the firm's management. Trading venues will be required to give historical data to testing platforms to ensure the resistance of trading and order-matching algorithms under strained market situations.
- Article 12(2)(c) of the MAR prohibits sending orders that would damage the functioning of trading venues' systems and produce or likely create misleading signals about the supply and demand for a financial product.
- When investment firms or trading venues notice suspicious trading behavior, they must immediately notify their regulator by submitting a Suspicious Order and Transaction Report.

3. CONCLUSIONS

To conclude, HFT has drastically changed the present financial market situation by integrating artificial intelligence-based models. The firms deploying HFT, are always competing among themselves and other participants to book better and faster returns. Regardless of the benefits, HFT is advertised negatively among the public and individual investors due to the risk it carries. As it is a recent innovation, there are very few regulations and policies across the globe over HFT. The existing policies are often criticized for not being stringent enough. Therefore, further research should focus on introducing different Artificial intelligence-based frameworks for trading exchanges to monitor HFT-based activities and to keep the interests of individual investors safe.

REFERENCES

Brogaard, Jonathan, Allen Carrion, Thibaut Moyaert, Ryan Riordan, Andriy Shkilko, and Konstantin Sokolov. "High-frequency trading and extreme price movements." Journal of Financial Economics 128, no. 2 (2018): 253-265.

Baldauf, Markus, and Joshua Mollner. "High-frequency trading and market performance." The Journal of Finance 75, no. 3 (2020): 1495-1526.

Van Kervel, Vincent, and Albert J. Menkveld. "High-frequency trading around large institutional orders." The Journal of Finance 74, no. 3 (2019): 1091-1137.

Brogaard, Jonathan, and Corey Garriott. "High-frequency trading competition." Journal of Financial and Quantitative Analysis 54, no. 4 (2019): 1469-1497.

Baron, Matthew, Jonathan Brogaard, Björn Hagströmer, and Andrei Kirilenko. "Risk and return in high-frequency trading." Journal of Financial and Quantitative Analysis 54, no. 3 (2019): 993-1024.

Linton, Oliver, and Soheil Mahmoodzadeh. "Implications of high-frequency trading for security markets." Annual Review of Economics 10 (2018): 237-259.

MacKenzie, Donald. "Material signals: A historical sociology of high-frequency trading." American Journal of Sociology 123, no. 6 (2018): 1635-1683.

Dalko, Viktoria, and Michael H. Wang. "High-frequency trading: Order-based innovation or manipulation?." Journal of Banking Regulation 21, no. 4 (2020): 289-298.

Ladley, Daniel. "The high frequency trade off between speed and sophistication." Journal of Economic Dynamics and Control 116 (2020): 103912.

Tilen, Č. U. K., and Arnaud Van Waeyenberge. "European legal framework for algorithmic and high frequency trading (Mifid 2 and MAR): A global approach to managing the risks of the modern trading paradigm." European Journal of Risk Regulation 9, no. 1 (2018): 146-153.

Briola, Antonio, Jeremy Turiel, Riccardo Marcaccioli, and Tomaso Aste. "Deep Reinforcement Learning for Active High Frequency Trading." arXiv preprint arXiv:2101.07107 (2021).

Tashiro, Daigo, Hiroyasu Matsushima, Kiyoshi Izumi, and Hiroki Sakaji. "Encoding of high-frequency order information and prediction of short-term stock price by deep learning." Quantitative Finance 19, no. 9 (2019): 1499-1506.

Ganesh, P., & Rakheja, P. (2018). VLSTM: Very Long Short-Term Memory Networks for High-Frequency Trading. arXiv preprint arXiv:1809.01506.

Zhou, Hao, and Petko S. Kalev. "Algorithmic and high frequency trading in Asia-Pacific, now and the future." Pacific-Basin Finance Journal 53 (2019): 186-207.

Rundo, Francesco. "Deep LSTM with reinforcement learning layer for financial trend prediction in FX high frequency trading systems." Applied Sciences 9, no. 20 (2019): 4460.

Gao, Kang, Wayne Luk, and Stephen Weston. "High-Frequency Trading and Financial Time-Series Prediction with Spiking Neural Networks." Wilmott 2021, no. 113 (2021): 18-33.

Goldblum, Micah, Avi Schwarzschild, Ankit B. Patel, and Tom Goldstein. "Adversarial Attacks on Machine Learning Systems for High-Frequency Trading." arXiv preprint arXiv:2002.09565 (2020).

Lanbouri, Zineb, and Said Achchab. "Stock Market prediction on High frequency data using Long-Short Term Memory." Procedia Computer Science 175 (2020): 603-608.

Crawford, Broderick, Ricardo Soto, Marco Alarcón San Martín, Hanns de la Fuente-Mella, Carlos Castro, and Fernando Paredes. "Automatic high-frequency trading: An application to emerging Chilean stock market. " Scientific Programming 2018 (2018).

Fang, Boyue, and Yutong Feng. "Design of High-Frequency Trading Algorithm Based on Machine Learning." arXiv preprint arXiv:1912.10343 (2019).

Arifovic, Jasmina, Xuezhong He, and Lijian Wei. "High Frequency Trading in FinTech age: AI with Speed." Available at SSRN 2771153 (2019).

Han, Henry, and Maxwell Li. "Big data analytics for high frequency trading volatility estimation." In Recent Developments in Data Science and Business Analytics, pp. 351-359. Springer, Cham, 2018.

Beverungen, Armin. "Algorithmic trading, artificial intelligence and the politics of cognition." In The Democratization of Artificial Intelligence, pp. 77-94. transcript-Verlag, 2020.

Aldrich, Eric M., and Kristian López Vargas. "Experiments in high-frequency trading: comparing two market institutions." Experimental Economics 23, no. 2 (2020): 322-352.

Seth, S., 2020. The World of High-Frequency Algorithmic Trading. [online] Investopedia. Available at: <https://www.investopedia.com/articles/investing/091615/world-high-frequency-algorithmic-trading.asp>.

Breckenfelder, J., 2020. Competition among high-frequency traders and market liquidity | VOX, CEPR Policy Portal. [online] Voxeu.org. Available at: <https://voxeu.org/article/competition-among-high-frequency-traders-and-market-liquidity>.

Gupta, A., 2015. Evolution of Algorithmic Trading, HFT and News Based Trading. [online] Blog.quantinsti.com. Available at: <https://blog.quantinsti.com/history-algorithmic-trading-hft/> [Accessed 27 October 2021].

Chen, J. and Daniel Jasperson, H., 2020. Algorithmic Trading Definition. [online] Investopedia. Available at: <https://www.investopedia.com/terms/a/algorithmictrading.asp>.

Chen, J., 2021. High-Frequency Trading (HFT) Definition. [online] Investopedia. Available at: <https://www.investopedia.com/terms/h/high-frequency-trading.asp>