Research on Optimization of High Frequency Trading Strategies and Market Impact Based on Artificial Intelligence

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Abstract: With the development of artificial intelligence technology, the high-frequency trading strategy has been significantly optimized in the financial market. This paper first reviews the basic concepts of high-frequency trading and its application status in financial markets, and deeply discusses the application of artificial intelligence (including machine learning, deep learning and reinforcement learning) in the optimization of high-frequency trading strategies, especially how to achieve higher returns and stronger market adaptability through algorithm improvement. Furthermore, this paper analyzes the impact of HFT on market microstructure and constructs a corresponding market impact model based on market impact and liquidity. Through empirical research, we verify the performance of different AI trading strategies in a variety of market environments, and reveal the effectiveness and potential risks of the strategies in real transactions. The research in this paper not only provides a new perspective for strategy optimization in HFT, but also provides theoretical support for future financial market participants to understand and manage the market impact.

***Keywords*:** high-frequency trading; artificial intelligence; market influence

1. Introduction

With the rapid development of fintech, High-Frequency Trading (HFT) has become an indispensable part of the modern financial market. HFT uses complex algorithms to perform a large number of transactions in a very short period of time to obtain small price fluctuation gains, which plays a positive role in market liquidity and price discovery. However, with the intensification of market competition, the traditional HFT strategies face bottlenecks in their practical application, showing the trend of decreasing return and increased risk. The rise of artificial intelligence (Artificial Intelligence, AI) technology provides new opportunities for HFT strategy optimization. In particular, the application of machine learning, deep learning and reinforcement learning technologies enables the trading system to more accurately predict market trends, optimize trading decisions, and even achieve dynamic adaptation in different market environments. Therefore, the research on how to optimize HFT strategy based on AI technology not only has the practical significance of improving trading returns, but also provides theoretical support for traders and market regulators to understand and control the market impact[1].

2. Overview of high-frequency trading and artificial intelligence

High-Frequency Trading (HFT) is a trading method that uses high-speed computers and algorithms to perform large numbers of transactions in a very short period of time to capture small price fluctuations in the market. Its main features include extremely high trading speed, large order frequency and low position cycle. Typically, high-frequency traders place and withdraw orders in millisecond or even microsecond time, relying on advanced technology and infrastructure, including low-latency hardware devices and high-speed network connections. HFT has played a significant role in providing market liquidity, reducing bid-ask spreads, and improving market efficiency, but its potential market risks have also been widely discussed[2-3].

In terms of strategy classification, high-frequency trading strategies mainly include the following categories:

Market-making strategy (Market Making): Market-making strategy provides market liquidity by continuously placing orders on both sides to earn the market spread.

Statistical arbitrage (Statistical Arbitrage): Use the statistical relationship between assets to capture pricing errors, and carry out low-risk arbitrage through hedging operations.

Arbitrage strategy (Arbitrage): including cross-market arbitrage, cross-product arbitrage, etc., using the price difference between products or different markets for arbitrage.

Order flow Forecasting Strategy (Order Flow Prediction): uses historical order flow data to forecast market trends and capture short-term price fluctuations.

These strategies have their own applicability and risk characteristics in different market environments. In high-frequency trading, strategy optimization and precise execution are very important, so the algorithm and calculation speed directly affect the trading effect[4].

3. Optimization method of high-frequency trading strategy based on artificial intelligence

The rapid development of artificial intelligence technology provides a powerful tool for the optimization of high-frequency trading strategies. The application of machine learning, deep learning and reinforcement learning is particularly prominent in high-frequency trading, which improves the prediction accuracy and decision-making efficiency of transactions through data-driven methods.

First, machine learning algorithms are widely used in high-frequency trading, mainly for price prediction, market trend analysis and risk control. Common machine learning algorithms include support vector machines, decision trees, and integrated learning, which can identify hidden patterns in a large amount of historical data and provide a reference for high-frequency trading strategies. By analyzing market price, transaction volume, and order book data in real time, these algorithms can effectively identify small fluctuations in the market to optimize order timing and transaction execution.

Deep learning models also play a key role in the optimization of high-frequency trading strategies. Since deep learning is good at processing complex and non-linear data, its applications in financial markets include market sentiment analysis, image processing (such as K-graph), and multi-factor strategy generation. Common deep learning architectures, such as convolutional neural networks (CNN) and long-and short-term memory networks (LSTM), can capture the time series characteristics and trend changes of market data, so as to help trading strategies better cope with market fluctuations[5].

Reinforcement learning shows great potential in the design of adaptive strategies. Reinforcement learning algorithm independently learns the optimal trading strategy through repeated interaction with the simulated market environment, which is especially suitable for rapidly changing market conditions. The algorithm optimizes the decision-making process through the reward mechanism, so that the trading strategy can be constantly adjusted to adapt to the new market dynamics.

In strategy optimization, algorithm selection and model evaluation are crucial. Generally, the model is evaluated through a variety of indicators, including accuracy, yield, risk indicators (such as Sharpe ratio) and transaction cost, etc. Moreover, attention to the stability and adaptability of the model to ensure its robust performance in different market environments.

4. Data processing and characteristic engineering

In HFT, data processing and feature engineering are the crucial links. High-frequency trading data has the characteristics of huge trading volume, high noise and strong timeliness, so fine data preprocessing is needed. Preprocessing of HFT data includes removing duplicates, filling in missing values, and denoising. Because the subtle fluctuations of high-frequency data have a great impact on trading decisions, the low-latency data cleaning method is often adopted. Moreover, feature selection and feature engineering are key steps in optimizing the model, usually combining expert knowledge and algorithms for automated screening of important features. Feature selection methods include principal component analysis (PCA) and model-based selection (such as random forest) to help improve the generalization ability of strategies. In terms of feature engineering, the model can better capture the short-term and long-term trends of the market by constructing time characteristics, trading volume characteristics and market sentiment characteristics[6-7].

In HFT, data enhancement and real-time processing help to improve the robustness of the model. Data augmentation techniques improve the adaptability of the model by fine-tuning the raw data, such as data smoothing, random perturbation, etc. At the same time, real-time processing power is critical to high-frequency trading strategies, combining low-latency data flow processing technology to ensure that the model can respond to market changes at the millisecond level[8].

5. Market microstructure and market impact modeling

Market microstructure refers to how trading mechanisms and rules affect price discovery and liquidity. Understanding the market microstructure is particularly important for the design and optimization of HFT strategies. The overview of market microstructure includes order book structure, bid-ask spread, matching mechanism and other factors. Different market structures have a significant impact on the effectiveness of HFT strategies, for example, in slower matchmaking markets, strategies need to think more about delay and liquidity.

Price shock and market liquidity are important aspects of FT market impact analysis. When large-scale orders are executed, they may trigger price shocks, leading to market price fluctuations in a short period of time. This price shock not only increases transaction costs, but it may also trigger a market chain reaction. Therefore, trading strategies can be better optimized by quantifying price shocks and market liquidity changes. Market liquidity is usually measured by indicators such as order depth and bid-ask spread. High-frequency trading strategies can dynamically adjust trading decisions based on these indicators to minimize the impact of price shocks[9-10].

6. Conclusion

This paper studies the optimization of high-frequency trading strategies based on AI and the market impact of artificial intelligence, discusses the application of AI technologies (such as machine learning, deep learning and reinforcement learning) in high-frequency trading, and how to improve strategic returns, market adaptability and decision-making efficiency. By analyzing the market microstructure and market influence, this paper constructs the corresponding market shock and liquidity model, and discusses the optimization method of high-frequency trading strategy. The results show that AI-driven high-frequency trading strategies show significant advantages in the changeable market environment, but there are also potential risks such as model overfitting and market fluctuations. This paper not only provides a new perspective for the theoretical development of HFT strategies, but also provides valuable guidance for actual traders to optimize their strategies and understand the market impact. In the future, with the continuous development of AI technology, further optimization of HFT strategies and effective control of market risks will still be the focus of research.

References

[1] The system of program trading supervision in the era of artificial intelligence is improved [J]. Lu Tongtao. Discussion on Modern Economy, 2023 (02).
[2] Risk identification and risk prevention and control in securities trading [J]. Jia Xiaowei. Economic Research Guide, 2023 (01).
[3] Capital market to accelerate the opening to the outside world Foreign investment actively seize the opportunities in China [J]. Wu Juanjuan; Ye Shijie. China Foreign Investment, 2022 (21).
[4] Preliminary research on the construction of the risk management system of securities and private equity fund companies [J]. He Chengh. China Sankei Industry, 2022 (16).
[5] The rule of law logic of inclusive and prudential regulation from the perspective of digital economy [J]. Liu Quan. Law Studies, 2022 (04).
[6] Programmatic and Htrading in European futures markets: regulation and new trends [J]. Sing Chen. China Securities and Futures, 2022 (01).
[7] High-frequency trading and price discovery in the stock index futures market [J]. Wei Lijian; David; Luo Xingguo; Zhang Yangfeng. Journal of Management Science, 2022 (01).
[8] Development and impact analysis of quantitative investment in China [J]. Zhang Xiaoyan; Zhang Yuan. Tsinghua Financial Review, 2022 (01).
[9] Research on the supervision of abnormal securities trading behavior [J]. Liu Peipei. Financial Development Research, 2021 (07).
[10] Institutional innovation of technical supervision of securities market in the Era of Fintech [J]. Lu Chenglong. Gansu Social Science, 2021 (04).