Impact of Quantitative Trading Strategies on Stock Investment Performance Under AI Empowerment

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Abstract. Against the complex and nonlinear characteristics of financial markets, traditional quantitative analysis has limitations in capturing stock price fluctuation patterns. Based on machine learning and quantitative trading, this paper constructs a research framework covering data processing, feature engineering, model construction and strategy back testing. Taking the CSI 300 Index as the research object, this paper uses the traditional dual moving average strategy as the benchmark and introduces the random forest algorithm to optimize trading signals. Subsequently, under a unified back testing framework, a comparative analysis is conducted on the investment performance of the baseline strategy and the AI-optimized strategy, evaluating the effectiveness of the strategies from both return capability and risk control dimensions. The findings indicate that, compared to traditional moving average strategies, the AI strategy optimized with the random forest model demonstrates superior performance in cumulative returns, annualized returns, and Sharpe ratio, while also showing a significant reduction in maximum draw-down and a more stable net value curve. This study proves that integrating machine learning with traditional quantitative strategies can improve the validity of trading signals and optimize risk-return characteristics, providing empirical reference for the application of AI in quantitative investment.

Keywords: Quantitative Trading, Random Forest, Trading Strategy, Investment Performance.

1 Introduction

With the development of information technology and the rapid growth of financial market data, quantitative trading is increasingly being applied in the stock market. Compared with traditional investment methods that rely on experience to make judgments, quantitative trading can utilize a large amount of market information for systematic processing, thereby improving the speed of decision-making and reducing the influence of human emotions on investment decisions. Machine learning, deep learning, and other algorithms have a strong ability to process financial data, predict market trends, and generate trading signals. Researchers have gradually paid attention to the integration of various technical indicators with machine learning models to strengthen the robustness and profitability of quantitative strategies [1]. Therefore, in

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the context of the rapid development of artificial intelligence technology, it is of great theoretical value and practical significance to study the quantitative trading strategy enabled by artificial intelligence and its impact on stock investment performance.

Quantitative trading strategies have a positive effect on improving the investment efficiency of the stock market, and to a certain extent, they optimize the risk-return characteristics of investment portfolios [2]. In recent years, most quantitative trading strategies have been constructed from the traditional perspective, that is, establishing trading models through technical analysis methods such as moving average strategies and momentum strategies, and identifying market trends and generating trading signals by analyzing historical price data. Relevant studies show that quantitative strategies based on technical indicators can achieve better investment returns in trending markets, but are prone to generating frequent trades and false signals in volatile markets. With the continuous development of artificial intelligence technology, more and more scholars have begun to apply machine learning methods to the research of financial market forecasting and quantitative trading. When neural network models are applied to stock return prediction, relevant results show that machine learning models can capture nonlinear correlations that traditional statistical methods cannot detect, thereby improving prediction accuracy [3]. In addition, algorithms such as random forest and support vector machines have been applied to optimize quantitative trading strategies, with machine learning methods used to screen trading signals, so as to enhance the stability and risk control capability of strategies. Overall, existing literature demonstrates that artificial intelligence technology can process high-dimensional data, identify market patterns, and optimize trading strategies. However, the current research still has certain limitations. On the one hand, most studies focus on the prediction accuracy of models and lack analysis of the actual performance of trading strategies. On the other hand, research gaps remain regarding how AI technology can effectively optimize traditional quantitative strategies.

Taking the Shanghai and Shenzhen 300 index as a sample, this paper constructs the basic double average strategy and the AI optimization strategy based on random forest, and compares them with each other. AI optimization strategy identifies market conditions through machine learning, eliminates invalid signals in volatile markets, and compares them from three aspects: returns, risks and risk adjusted returns. This study deepens the application of AI in quantitative trading in theory, and promotes the integration of traditional strategies and machine learning. In practice, it provides a reference for investors to optimize strategies and improve performance.

2 Theory and Model

The theoretical basis of quantitative trading is modern financial theory and technical analysis theory. Modern financial theory believes that price changes contain analyzable information, while technical analysis theory advocates that price trends have trends and regularity, and market trends can be judged through historical data. Based on this, with the development of artificial intelligence technology, machine

learning methods have been gradually introduced into quantitative trading research. These methods are trained on a large amount of historical data to identify hidden complex patterns, thereby improving the prediction accuracy and stability of trading strategies [4].

The biggest contribution of artificial intelligence to quantitative trading is the ability to process data and perform pattern recognition. Machine learning algorithms can process high-dimensional data and identify nonlinear relationships within it, a characteristic that is of great significance for analyzing the complex information structure of financial markets [5]. Secondly, machine learning identifies similar scenarios to generate better signals by training price characteristics under different market conditions. At the same time, the use of AI model to classify or probability predict trading signals can filter out false signals and improve the stability of strategies. Therefore, the combination of AI and traditional quantitative strategies helps to make up for the shortcomings of technical analysis and realize strategy optimization. The moving average strategy and momentum strategy commonly used in quantitative trading construct trading signals through moving average crossing and historical yield ranking respectively, but they only perform well in the trend market and are easy to produce noise signals in the volatile market, resulting in frequent trading and declining returns.

To improve the effectiveness of the strategy, a machine learning model is introduced to optimize the traditional moving average strategy. Specifically, this paper constructs multi-dimensional technical indicators as input features, applies the random forest algorithm to identify price change patterns under different market conditions, and extracts valid price change patterns from the model outputs. Random forest uses the method of decision tree integration to establish a machine learning model, which uses bootstrap sampling to generate multiple decision trees, and then votes to determine the final results. This algorithm has strong nonlinear fitting capability and can avoid the overfitting phenomenon of a single model to a certain extent. Therefore, it is widely used in financial data analysis and delivers superior back test performance in the construction of multi-factor quantitative strategies. In this paper, the random forest model is applied to filter the trading signals generated by the traditional moving average strategy, so as to reduce the probability of false breakthrough signals and improve the reliability of trading decisions. This theoretical framework lays the foundation for the subsequent data processing, model construction, and strategy back test analysis.

3 Data Processing and Modeling

3.1 Data Sources and Pre-Processing

The research data in this paper come from the CSMAR database, and the Shanghai and Shenzhen 300 index (Code: 000300) is selected as the research target. The risk-free interest rate data adopts the daily data of the benchmark interest rate of one-year fixed deposits published by the People's Bank of China. From January to April 2023, the adjustment of the CSI 300 Index constituents resulted in missing data for some

trading days, and the data for this period were excluded. The remaining missing values on trading days are filled using the weighted average of the data from the 5 trading days before and after the missing date. The second step is outlier detection. Based on the 3-sigma truncation principle, values below μ-3σ are corrected to μ-3σ, and values above μ+3σ are corrected to μ+3σ. Extreme values exceeding three times the standard deviation from the mean are marked and verified to ensure data quality. The third step is data alignment and standardization. Stock data and risk-free interest rate data are matched by trading date to ensure the consistency of the two-time series.

As seen in Table 1, MA5, MA20, MA60, momentum 20 and volatility 20 are selected as the input characteristics of the model, and excess returns are defined as daily returns minus daily risk-free interest rates. During the sample period, the average daily return of the Shanghai and Shenzhen 300 index was only 0.03%, with a median of 0.05%, and there was no obvious trend. The standard deviation of daily yield is 1.08%, the largest decline is -7.05%, the largest increase is 8.48%, showing the characteristics of peak thick tail and volatility agglomeration. The statistical characteristics of the moving average and the closing price are similar, indicating that the market as a whole is in a volatile pattern, and the trend signal is easy to be confused with noise, which provides a practical basis for the introduction of AI filtering mechanism.

Table 1. Descriptive statistics of main variables.

Variables	Sample size	Mean	Standard deviation	Minimum	Median	Max
Closing price	707	3886.93	414.07	3159.25	3854.12	4790.69
Daily yield	707	0.0003	0.0108	-0.0705	0.0500	0.0848
MA5	707	3885.20	410.38	3176.92	3852.33	4770.77
MA20	707	3877.81	396.29	3240.47	3850.15	4737.57
MA60	707	3860.22	358.22	3349.89	3842.68	4669.80
Momentum 20	707	0.0056	0.0506	-0.0899	0.3200	0.2814

3.2 Strategy Building and Back Testing Settings

This paper compares the basic moving average strategy with the AI optimization strategy. The basic moving average strategy adopts the double moving average cross model of MA5 and MA20, and the transaction is executed at the opening price of the next trading day after the signal is triggered. The strategy has simple logic, but it is prone to false breakthrough signals in volatile markets, resulting in repeated stop losses, which has become the main motivation for the introduction of AI optimization. AI optimization strategy uses random forest algorithm to filter the basic strategy signal. With the development of AI forecasting technology, financial market forecasting methods are transitioning from traditional statistical modeling to deep learning and large-scale artificial intelligence models [6]. AI-enabled quantitative trading identifies nonlinear characteristics through machine learning algorithms to

capture short-term market opportunities [7]. Random forest aggregates multiple decision trees through bootstrap and outputs classification results through a voting mechanism, which has both nonlinear fitting ability and anti-overfitting characteristics [8].

Taking the positive and negative cumulative excess returns in the next 5 days as the label, MA5, MA20, MA60, 20-day momentum and 20-day volatility are selected as the characteristic variables. The super parameters are determined by grid search: the number of decision trees is 100, the maximum depth is 10, and the minimum number of split samples is 5. The training set and the test set are divided according to the 7:3 sequence to avoid future information leakage. In signal optimization, the original signal of the basic moving average strategy is calculated first, and then the five-dimensional characteristics of the current market are extracted and input into the random forest model to obtain the rising probability p, and 0.6 and 0.4 are set as thresholds: P>0.6 to confirm buying, P>0.4 to confirm selling, between which the filtered signal and position remain unchanged. The mechanism identifies high winning opportunities through machine learning and effectively reduces invalid transactions in volatile markets.

The two strategies are back tested under the same framework, with an initial capital of 1 million yuan and a back-test interval from May 2023 to March 2026, avoiding the missing period before data cleaning to ensure sample integrity. Transaction costs are accrued at a unilateral rate of 0.1%, with reference to the actual trading rate in China's A-share market. Trades are executed at the opening price of the next trading day after the signal is generated. Full positions are held after buying, and cash positions are held after selling, so as to enhance the reference value for actual trading. Performance evaluation is carried out from two aspects of income and risk, and the income indicators are cumulative yield and annualized yield. The maximum withdrawal and annualized volatility are selected as risk indicators. At the same time, the Sharpe ratio is used to measure risk-adjusted returns.

4 Model Empirical Effect Analysis

4.1 Cumulative Income Comparison

As shown in Fig. 1, the cumulative returns of the two strategies are significantly different during the sample test period, which is from July 2024 to March 2026. The net value trend of the two strategies is obviously differentiated, and the decline defense stage is 7-8 in 2024, with the lowest net value of the basic strategy falling to 883000 yuan and the largest withdrawal of 11.7%. The net value of AI strategy remained above 985000 yuan in the same period, with the maximum withdrawal of only 1.5%. The trend capture stage spanned from September to November 2024. The AI strategy identified the trend turning point in early September, with its net value climbing to 1.264 million yuan. The basic strategy lagged in trend confirmation, with a net value of 1.052 million yuan in the same period, and the gap between the two widened to 212,000 yuan. The shock consolidation stage is from January 2025 to March 2026, and the net value of the AI strategy fluctuates in a narrow range of 1.35-

1.38 million yuan, with an annual volatility of 9.8%. Although the basic strategy rebounded to 1.302 million yuan, it withdrew more than 8% twice during the period. By the end of the period, the cumulative yield of the AI strategy was 37.8%, the basic strategy was 30.2%, and the excess return was 76000 yuan, a relative increase of 28.6%. The above results show that an AI optimization strategy can effectively capture market opportunities in the rising stage, show stronger defensive ability in the falling and volatile stages, and achieve the goal of rising more and falling less.

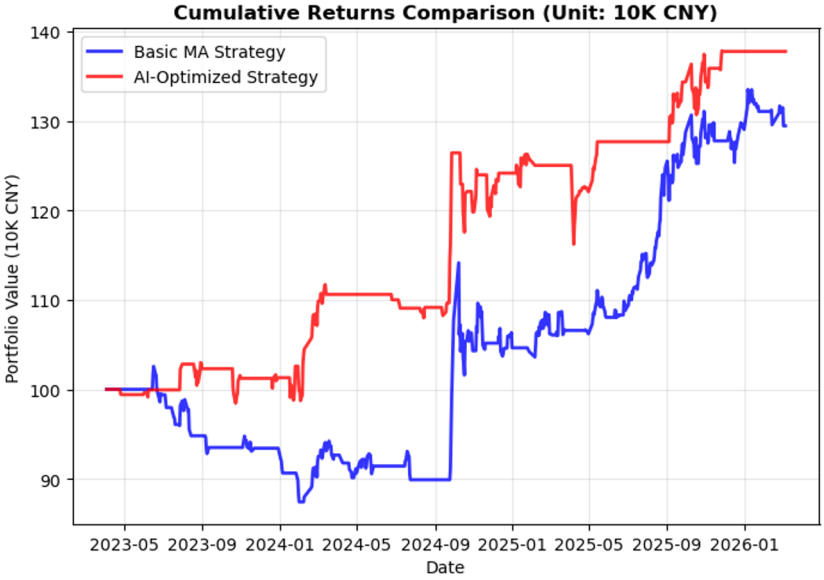


Fig. 1. Comparison of cumulative return curve (Picture credit: Original).

4.2 Risk Control Effect

As shown in Fig. 2, the drawdown performance of the two strategies differs significantly during the back test period. The basic strategy recorded a maximum drawdown of -14.77% in January 2024, and the drawdown lasted for 3 consecutive months. The maximum withdrawal of the AI strategy in the same period is only -8.07%, and the withdrawal repair time is shorter, usually returning to the previous high point within 1-2 months. In terms of withdrawal frequency, the withdrawal of more than -5% of the basic strategy occurred six times, and the AI strategy only three times. From the perspective of withdrawal depth, the withdrawal range of the AI strategy is higher than that of the basic strategy as a whole, and the net value curve is smoother. This difference stems from the filtering mechanism of the random forest model. In the early stage of market turbulence or decline, the model identifies weak trend features through technical indicators, suppresses the generation of invalid trading signals, and effectively avoids repeated stop losses of the basic strategy caused by false breakthroughs. The improvement of risk control ability is the key to the improvement of the Sharpe ratio of the AI strategy.

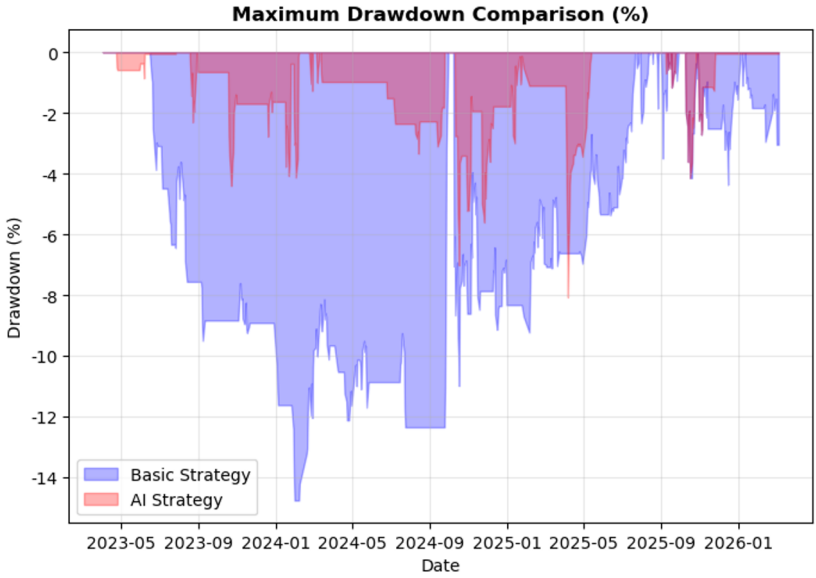


Fig. 2. Comparison of maximum withdrawal (Picture credit: Original).

4.3 Income Distribution Characteristics

The daily yield distribution reflects the stability of strategic returns and extreme risk exposure. The standard deviation of the AI strategy was 1.08%, which was 25.5% lower than that of the basic strategy. Skewness -0.32, closer to symmetry than the basic strategy. The kurtosis is 3.45, and the peak is more concentrated. The Jarque BERA test showed that both strategies rejected the original hypothesis of normal distribution, but the AI strategy Statistics were significantly smaller than the basic strategy. Quantile analysis shows that the AI strategy is 5% quantile -1.52%, the basic strategy 2.31%, and the downside risk is lower. This distribution feature effectively reduces the irrational redemption behavior caused by short-term, large withdrawals.

From the perspective of key performance indicators, the AI strategy outperforms the basic strategy in both return and risk dimensions. In terms of cumulative returns, the cumulative yield of the AI strategy reached 37.8%, 8.4 percentage points higher than that of the basic strategy at 29.4%, representing a relative increase of 28.6%. In terms of annual returns, the AI strategy reached 12.1%, an increase of 2.5 percentage points over 9.6% of the basic strategy. In terms of the Sharpe ratio, the AI strategy is 1.05, and the basic strategy is 0.69, an increase of 52.2%, indicating that the risk-adjusted return of the AI strategy is significantly dominant, which is the core finding of this study. In terms of withdrawal control, the maximum withdrawal of the AI strategy is 45.3% lower than that of the basic strategy, and the risk control ability is outstanding. The above results show that the AI optimization strategy achieves the collaborative optimization of improving the win rate and reducing loss magnitude through the signal filtering mechanism of the random forest model, and verifies the core value of machine learning methods in quantitative trading.

5 Conclusion

Taking the Shanghai and Shenzhen 300 index as the research object, this paper makes an empirical analysis of the application effect of artificial intelligence technology in quantitative trading by constructing the traditional double average trading strategy and AI optimization trading strategy. The results show that compared with the traditional moving average strategy, the AI strategy after introducing a random forest model for signal filtering performs better in investment performance. From the perspective of return indicators, the cumulative yield and annualized yield of the AI optimization strategy are higher than those of the basic strategy, which can more effectively capture trend opportunities in the market uptrend stage. From the perspective of risk indicators, the maximum drawdown of the AI strategy is significantly lower than that of the basic strategy, with a more stable net value curve, indicating that it has stronger risk defense capability during market turbulence or decline. In addition, the AI model effectively reduces the losses caused by frequent exchanges in volatile markets by identifying the characteristics of market conditions and screening the original trading signals, thus improving the overall stability of the strategy. On the whole, the combination of machine learning methods and traditional quantitative trading strategies can improve the effectiveness of trading signals to a certain extent and realize the coordinated optimization of income improvement and risk control. Therefore, in actual investment practice, investors can introduce artificial intelligence algorithms based on traditional technical analysis strategies to assist in evaluating and optimizing trading signals, so as to improve the overall performance of quantitative trading strategies.

Although this paper makes a preliminary discussion on the quantitative trading strategy enabled by artificial intelligence, there are still many shortcomings. For example, this paper takes the Shanghai and Shenzhen 300 index as a sample. The sample size is small, and the sample can be further expanded to study more indexes or individual stocks, so as to test whether the model is effective in various market environments. The technical variables selected in this paper are mainly technical indicators, which do not include macroeconomic variables, market sentiment variables, financial text information, and other factors that can affect stock returns. In future research, more data types can be added to improve the ability of the model to depict market information. In addition, the machine learning algorithm, random forest, used in this paper, although it has high stability and strong explainability, is being more and more widely used with the continuous development of artificial intelligence technology. Future research can explore different machine learning algorithms, especially in quantitative asset trading scenarios, and further examine quantitative prediction models and their corresponding investment returns, so as to more clearly clarify the broad application prospects of artificial intelligence technology in the field of financial investment.

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