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Research on Financial Quantitative Trading Based on Hybrid DEA Data Envelopment Analysis and Integrated System Modeling

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Abstract: *This article deals with the analysis and fine-tuning of financial quantitative trading strategies which are developed by a hybrid approach involving both DEA (Data Envelopment Analysis) and integrated system modeling. Firstly, DEA is employed in the design of a performance evaluation model that measures the risk-return efficiency of several strategies. Subsequently, there is a description of the integrated system modeling application which is used to do the mode of movement (technical trend) and behavior of the trades on the financial market, which are the natural interactions in the system. Research results show that the hybrid model overshadows traditional single models in terms of prediction accuracy, risk control, and strategy selection, laying the ground to the best of both the new theoretical and practical developments in financial quantitative trading.*

Keywords: *Financial Quantitative Trading; Data Envelopment Analysis (DEA); Integrated System Modeling; Hybrid Model; Empirical Research*

1. Introduction

With financial markets' ever-growing intricacy and the rapid advancement in the field of technology, quantitative trading has now moved to the spotlight as one of the prevailing investment strategies. Quantitative trading uses mathematical models and data analysis to make trading decisions, but traditional models have limitations in handling complex markets. DEA and integrated system modeling offer new approaches to address this issue. DEA is used to assess the efficiency of trading strategies, while integrated system modeling helps simulate the dynamic changes of markets. This study combines DEA and integrated system modeling to propose a more comprehensive method for evaluating the efficiency of quantitative trading strategies. This research study targets to assess and to optimize trading strategies by using DEA and to create market adaptability and risk control improvement by the knowledge gained. This article will also include design and application of the proposed method, and also, it will analyze the empirical results.

2. Current Research on Financial Quantitative Trading

Currently, the financial market and information technology are taking the lead in financial quantitative trading. Quantitative trading encompasses data analysis, statistical approaches, computer algorithms to process market data, and, therefore, to make trading decisions based on science. Nevertheless, traditional quantitative trading models frequently have limitations, especially when it comes to dealing with nonlinear and complex market environments now. Accordingly, more research has been carried out to optimize trading strategies via combining various methods to enhance prediction accuracy and risk control. DEA, as a mathematical tool for the relative efficiency, is an important one in the financial field to examine the efficiency of different trading strategies. The DEA method allows traders to optimize the choice of their strategy. Using machine learning algorithms hand in hand with the traditional quantitative trading models, the hybrid approach, has been gaining more and more popularity, for example, reinforcement learning is used to improve trading strategies. In addition, big data-based trading signal recognition is regarded as one of the most prepare in the corresponding research[1].

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3. Research Methodology

3.1. Theoretical Framework Construction

Financial quantitative trading is a crucial area in financial studies, requiring a robust theoretical framework to properly assess and optimize trading strategies. Figure 1 illustrates a practical framework that combines a Balanced Scorecard (BSC)-based strategic goal evaluation with Data Envelopment Analysis (DEA) for efficiency measurement, offering a comprehensive foundation for quantitative trading optimization. The figure highlights five key strategic areas—Growth and Learning, Internal Processes, Customer, Social Responsibility, and Finance—with both continuous and discrete input and output indicators to facilitate micro and macro evaluations of trading strategies[2]. This comprehensive approach leverages the Balanced Scorecard to address financial targets, customer satisfaction, process efficiency, and social responsibility within strategic management.

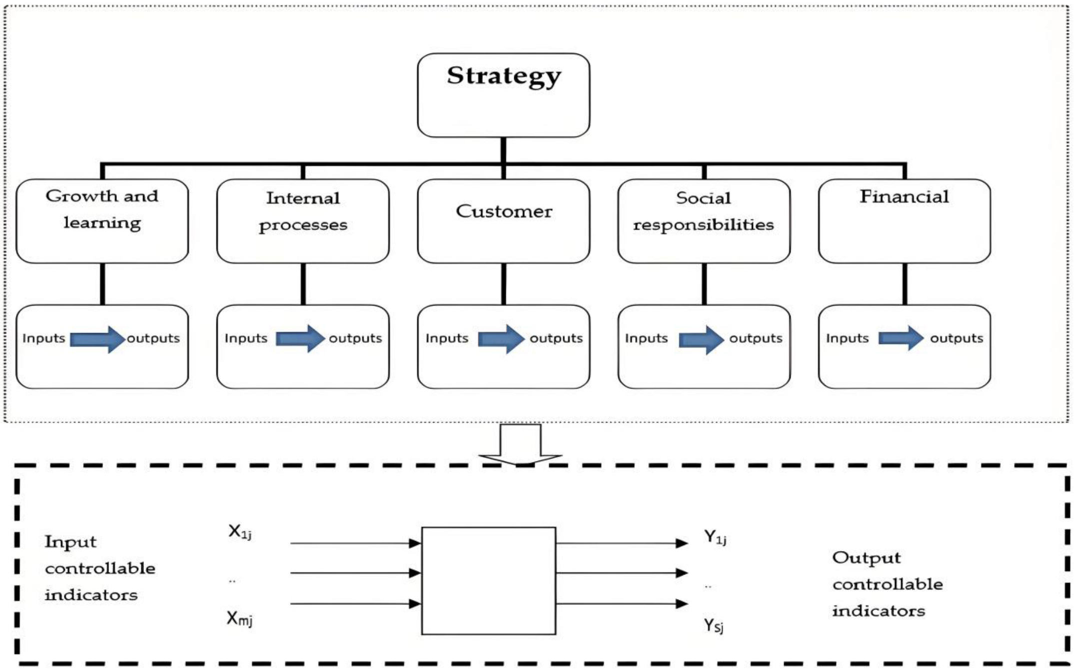

Figure 1: Strategic Goal and DEA Performance Evaluation Framework Based on the Balanced Scorecard

The DEA method serves as a powerful efficiency evaluation tool by using input-output data to measure the performance of various trading strategies. It primarily employs controllable input indicators, such as capital investment and market research, to compare strategies and determine efficiency frontiers for optimization. By integrating the multi-dimensional evaluation objectives of the Balanced Scorecard with DEA's efficiency measures, this study constructs a multi-layer evaluation model that enhances resource allocation, minimizes risk, and maximizes returns in quantitative trading strategies[3].

3.2. Data Sources and Preprocessing

High-quality and precise data are crucial for assessing and optimizing trading strategy models in quantitative financial trading. The selection of data sources and proper preprocessing are essential for model validity. This research covers various markets, including options and stocks. Historical stock data include prices (opening, closing, high, low), transaction volumes, and deal amounts, which reflect basic trading activity. Additionally, macroeconomic factors such as GDP, inflation rate, interest rates, and exchange rates are incorporated, as they greatly influence market trends and strategy optimization. Company fundamentals—such as price-to-earnings ratio, profit growth rate, and debt ratio—are used to assess stock value, while high-frequency trading strategies rely on real-time data (minute-by-minute price changes, volumes, and order book details) to capture short-term trends[7].Data preprocessing is vital since financial data often contain missing values, noise, and outliers that can impair model performance. Data cleaning begins by identifying missing values, which are either imputed using

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interpolation or removed if unfillable. Noise reduction techniques, like moving averages, stabilize the data for long-term analysis. Standardization using the Z-score method and normalization via min-max scaling ensure data consistency. Feature selection and dimensionality reduction (using L1-regularization and PCA) remove redundancies while preserving key market dynamics. Finally, differencing is applied to achieve stationarity by eliminating trends and seasonality[4].

4. Model Construction and Algorithm Implementation

4.1. DEA Model Design

The Data Envelopment Analysis (DEA) model is an effective tool for evaluating the relative performance of various trading strategies in a cost-efficient manner. Figure 2 outlines its structure, where input and output indicators are categorized as controllable and uncontrollable to better reflect real-world trading conditions. The DEA model is built on two main principles. First, controllable input indicators, such as capital investment, transaction frequency, and technical support, are used to enhance trading strategies. Second, performance outputs—like return and profitability—are measured using fixed models. Additionally, the model incorporates uncontrollable parameters (IAM and OAM) to assess strategy efficiency under varying market conditions and macroeconomic influences.[5].

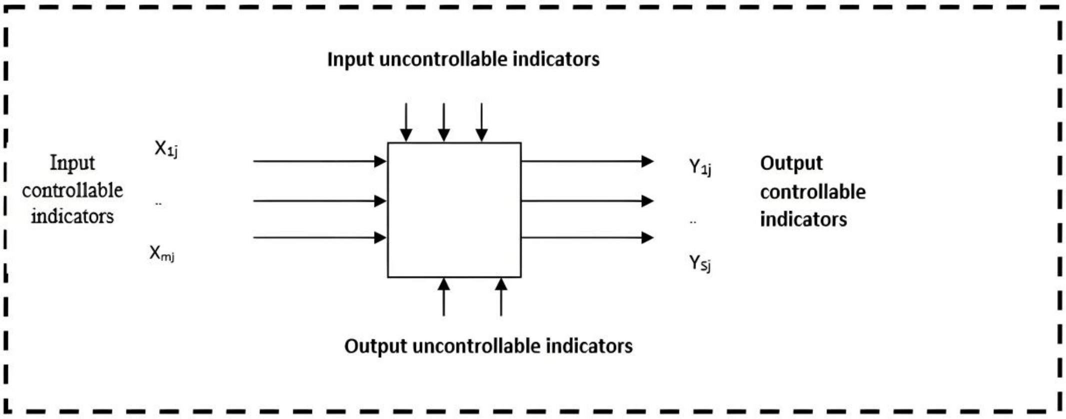

Figure 2: DEA Model Input-Output Structure

In Figure 2, controllable input indicators (e.g., capital investment, risk management) feed into the DEA model, while controllable output indicators (e.g., returns, profitability) emerge as outputs. Uncontrollable indicators are also integrated to quantify external impacts. By comparing inputs and outputs across multiple dimensions, the DEA model determines the relative efficiency of each trading strategy through mathematical optimization. This approach identifies potential resource wastage and areas for improvement, enabling traders to select, modify, and optimize strategies for maximum return and optimal performance in practical applications.

4.2. Algorithm Implementation and Solution Methods

In the study, mathematical optimization is used to find the optimal solution and compare the efficiency of different quant trading strategies. DEA's primary objective is to use linear programming methods to increase the efficiency of every decision unit (for instance, trading strategies). This is achieved by the application of the already proven models such as the CCR model (Charnes, Cooper, and Rhodes Model) and the BCC model (Banker, Charnes, and Cooper Model) among others, to ensure an effective evaluation and optimization.CCR is the simplest form of data envelopment analysis and it is direct towards a linear programming problem which is to be solved to evaluate the relationship between outputs and inputs. In other words, it is practically the most efficient combination of inputs that each decision unit (trading strategy) uses to derive outputs. For a given decision unit ii, the goal is to due the function value is maximized The exact expression is as shown in Formula 1:

$$\max \theta_i = \frac{\sum_{r=1}^{s} \lambda_r y_{rj}}{\sum_{m=1}^{m} \lambda_m x_{mj}} \tag{1}$$

where y_{rj} and x_{mj} are the r-th output and the m-th input of the j-th decision unit, respectively, λ_r and λ_m are optimization variables representing the weight of each decision unit in the model. By

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solving this linear programming problem, we can obtain the relative efficiency of each decision unit. The constraint condition is as shown in Formula 2:

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2}$$

This constraint ensures the feasibility of the model and prevents excessive weighting.

In the CCR model, constant returns to scale (CRS) are assumed, but in practical applications, scale effects are often variable. The BCC model extends the CCR model by allowing for variable returns to scale (VRS), which more accurately reflects the actual effectiveness of trading strategies. The objective function of the BCC model is similar to that of the CCR model but adds an adjustment term θ_i to account for scale effects as shown in Formula 3:

$$\sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1,2,\ldots,n \tag{3}$$

By solving the BCC model, we can conduct a more detailed evaluation of quantitative trading strategies while considering scale effects.

To enhance the adaptability of the DEA model under diverse input-output conditions, we introduce the concept of data weighting. In practical trading strategies, different input and output indicators have varying impacts on the final decision. Therefore, we assign weights w_m and w_r to each input and output indicator, respectively, and solve the optimal strategy's efficiency using a weighted optimization algorithm. The objective function after data weighting is as shown in Formula 4:

$$\max \theta_i = \frac{\sum_{r=1}^{s} w_r \lambda_r y_{rj}}{\sum_{m=1}^{m} w_m \lambda_m x_{mj}} \tag{4}$$

where w_m and w_r are the weights for each output and input, reflecting their relative importance in the strategy evaluation. These weights can be adjusted according to the characteristics of market data and strategy goals, improving the model's accuracy and application flexibility.

The DEA model, in the practical solving processes, commonly uses linear programming algorithms that are processed point to (for example, the simplex method or interior-point technique. To enhance solution efficiency, especially when there are a large number of decision units and complex data, the optimized numerical solving methods such as the Branch and Bound Method or efficient iterative optimization algorithms can be used.

5. Empirical Analysis

5.1. Sample Data Description

To analyze and refine financial quantitative trading strategies, we employed numerous data samples from various financial markets. The data includes stock market trading information, macroeconomic indicators, and company fundamentals. Covering the period from January 2018 to December 2023, the dataset spans multiple economic cycles, enabling the model to generate robust strategies for different market conditions. Data were sourced from providers such as Wind and Yahoo Finance, as well as publicly available macroeconomic databases. All data underwent rigorous preprocessing for quality control, including the removal of missing values, outliers, and normalization to ensure consistency and comparability.The Table 1 below highlights key items extracted from the sample data, representing historical stock trading data, company fundamentals, and macroeconomic indicators.

Table 1: Sample Data Table

Field	Data Source	Description	Example Data
Date	Wind, Yahoo Finance	Trading date	2020-01-01
Stock Code	Wind	Unique identifier for each stock	000001.SZ
Opening Price	Wind, Yahoo Finance	Price at market open	10.25
Closing Price	Wind, Yahoo Finance	Price at market close	10.50
Trading Volume	Wind, Yahoo Finance	Daily trading volume	500,000

By analyzing these data samples, we optimized model parameters, enhanced trading efficiency, and improved returns in quantitative trading strategies.

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5.2. DEA Model Empirical Results

The study was intended to test the performance of these different quant trading strategies based on the DEA model. Both the CCR model and the BCC model were used for assessing the performance of each strategy in relation to time and market environment. The findings indicate that for the strategies to be efficient, there must be an intense connection with such factors as capital investment, risk management input, and market research input.Using the CCR model, it was evident that short-term high-frequency trading strategies had high DEA efficiency values, around 1, which shows a strong performance both with capital and market research input. However, long-term value investment strategies had lower efficiency values, which could be related to lower capital input and longer investment cycles. At the same time, the interaction effect between the DEA result and the equity component is significant, too. Finally, As the Figure 3 shown, the strategic atretagy of cross-market arbitrage with high efficiency in both models and it is of particular note to the BCC model, where with larger scales of operations the efficiency levels of this strategy become higher seen as a scale effect innovation.

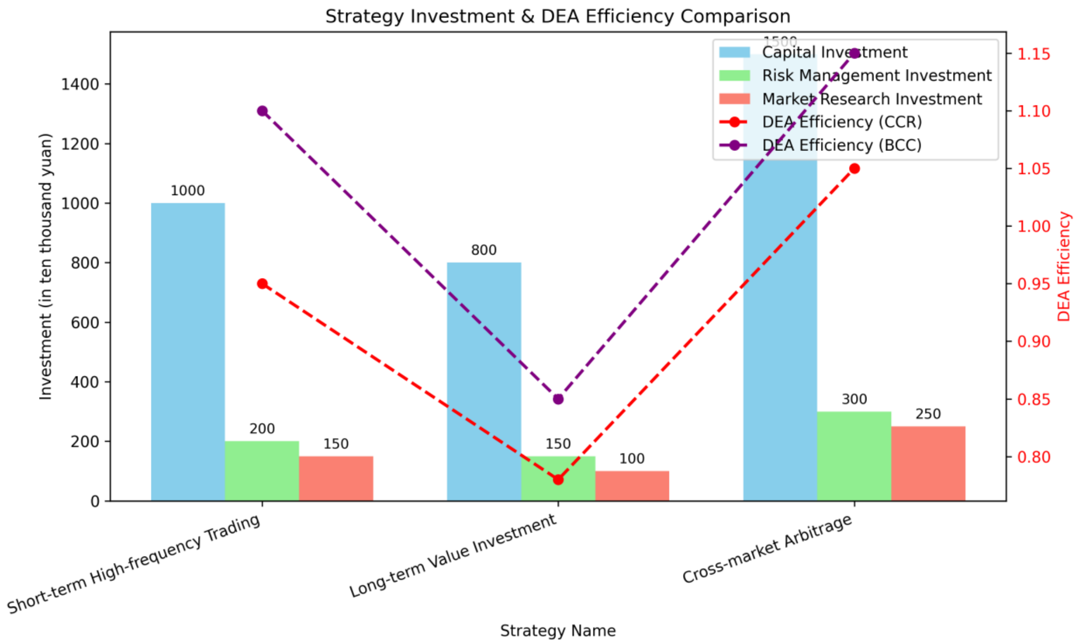

Figure 3: Strategy Investment & DEA Efficiency Comparison

It is indicated that short-term high-frequency trading and cross-market arbitrage strategies benefit from the investment of capital and market research leading to higher efficiency. On the other hand, long-term value investment strategies demonstrate lower efficiency due to less investment in these areas. Additional analysis applied using the BCC model reveals that scale effects contribute to the cross-market arbitrage strategies as their efficiency increases when capital expands. In a word, the DEA model can expound on the effectiveness of different trading strategies relative to the inputs and how they help in decision-making support, therefore, strategy optimization and resource allocation are possible.

5.3. Integrated System Modeling Simulation Analysis

The study under discussion herein uses an integrated system modeling approach that is employed to further discuss varied quantitative trading strategies' performance. The combination of system dynamics modeling and DEA efficiency evaluation enabled the researchers to build a complete simulation framework that could help in the evaluation of strategies in a wiggly market. Simulation analysis showed how the strategies were following the market variables which then lead to the questions of their efficiency under different conditions.During the simulation, various market variables were programmed; capital flow, volume of trading and market volatility. Is the effect of market variables on trading strategies being taken into account using system dynamics models? The simulation results demonstrate the fact that a strategy's capacity to create positive financial returns is not only governed by capital but also by market volatility. Also, the strategy's performance is based on risk management mechanisms. This is particularly true in high-volatility markets where some high-frequency trading strategies showed resilient features in addition to long-term investments, which were stable but had lower returns.The following is the Figure 4 detailing the major results from the integrated system modeling simulation analysis:

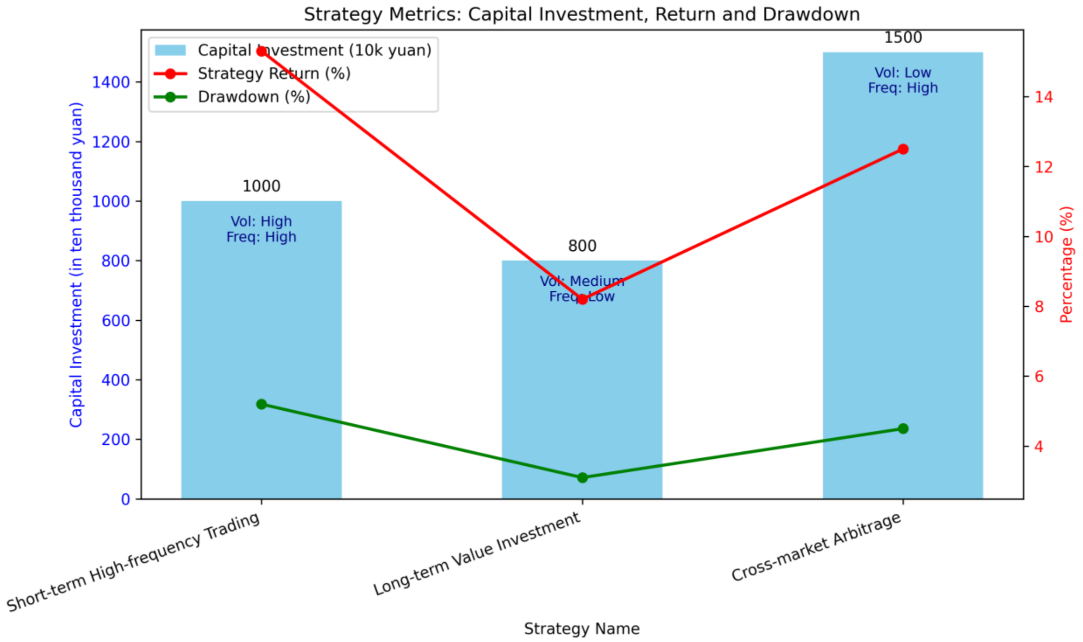

Figure 4: The major results from the integrated system modeling simulation analysis

Analyzing the Figure 4, it is evident that in markets with high volatility, the investment strategies that had short-term high-frequency trading did over 25 provided higher returns and lower drawdowns respectively, which meant that their positions later got closed on a positive note and they "bagged" a profit margin. It also shows that they had the capacity to quickly reorient themselves to market conditions and therefore make relatively high returns. However, even though Value investing strategies generate lower returns, their risk is also much lower which means that they are capable of maintaining lower risk in a stable market such as the current bull market. Cross-market Styles in the low-volatility markets were more focused on more rewarding wind up with the more and less drawdown, what it means is that they were able to benefit from the stability of the markets to which they were exposed.This study uncovered a quantitative trading algorithm that was tested by a comprehensive system modeling simulation to see the dif for the first time though the different strategies showed different results. The models were then validated. Being the most efficient and reliable foundation of further optimizing and tuning trading strategies, the system modeling approach gives quantitative traders a competitive edge over their competitors in down-dynamic market situations, where they can thus achieve proper resource allocation and strategy adjustments through the means of integration of system models.

5.4. Hybrid Model Performance Evaluation

This research, in which Data Envelopment Analysis and the integrated system modeling approach are combined were used to evaluate the merits of varied quantitative trading strategies in a comprehensive way. By means of the combination of DEA evaluation of the efficiency with the integrated systems modeling of the simulation, we were able to adjust and optimize investments in trading strategies from varying points of view. This framework considering not only capital investment but also control of excess risk and market volatility enables better understanding the relative performance of each strategy in complex markets. The empirical results of the hybrid model imply the superiority of the hybrid model in comparison to the single DEA or the integrated system modeling methods in terms of adaptability and accuracy of efficiency evaluation and strategy optimization. More specifically, the hybrid model not only compares the relative efficiency of strategies but also creates the model that describes the dynamic performance of the strategies under possible market downturns and various economic cycles. In high-volatile markets, the hybrid model revises strategy weighting and input-output relationships better and thereby boosts performance in general.The Figure 5 below delineates the efficient performance of the hybrid model through a comparison with the single DEA model:

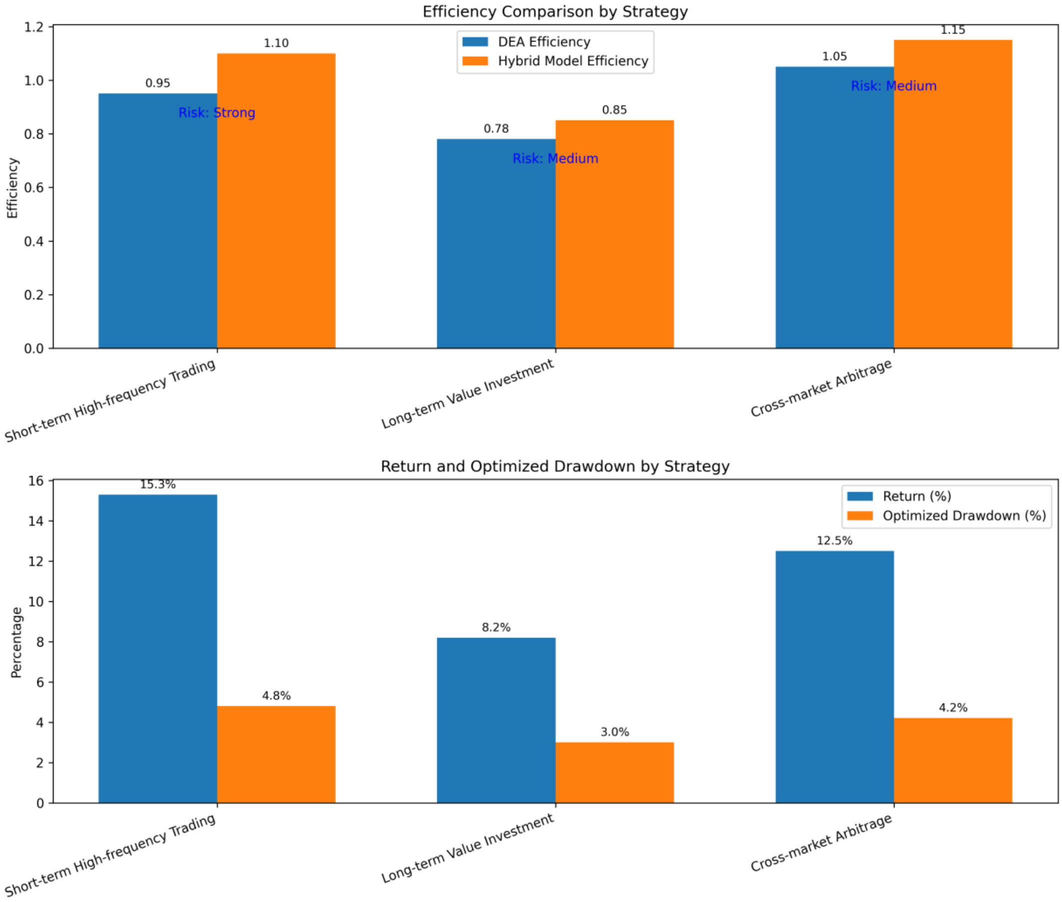

Figure 5:The efficient performance of the hybrid model

As can be seen from the Figure 5, the efficiency evaluation by a fusion DEA model is more superior to the single DEA model. It was found that the optimization of short-term high-frequency trading and cross-market arbitrage strategies led to significant increases in return and better control over risks. Through this, the decline in short-term high-frequency trading has gone from 5.2% to 4.8%, thereby exposing the hybrid model that has edge over risk control. The optimization of cross-market arbitrate also contributed to the model's better performance by ending up with higher returns and lower drawdowns. The hybrid model is strong because it allows the user to change the strategy inputs and outputs so it can adjust to the market conditions which are sometimes unstable. What's more, by such a mix of the static efficiency evaluation of DEA and the dynamic simulation of the integrated system modeling, the hybrid model provides a much more thorough and scientific way of optimizing quantitative trading strategies. With this model, it is no longer necessary to sacrifice the amount of money you get for your strategy for the control of risks since no matter what the market conditions are, this will be easier with the help of it.

6. Conclusion

This study was a detailed assessment of the effectiveness and function of the varied quantitative trading strategies by the DEA model and integrated system modeling approach. The empirical analysis exhibits that capital investment, risk management, and market research are the most crucial factors that affect the efficiency of trading strategies. Short-term high-frequency trading strategies, especially with high capital investment and in volatile markets, show super performance. Long-term investment strategies are the ones which have the lowest drawdowns during stable market conditions and thus suitable for conservative investments. The integrated system modeling simulation further proved that different strategies are applicable in dynamic market environments and this was represented with the information that high-frequency trading performs better in volatile markets, while cross-market

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arbitrage is more efficient in low-volatility markets.

References

[1] Amirteimoori, Alireza, et al. "On the environmental performance analysis: a combined fuzzy data envelopment analysis and artificial intelligence algorithms." Expert Systems with Applications 224 (2023): 119953.

[2] Panwar, Ankita, et al. "A review on the 40 years of existence of data envelopment analysis models: Historic development and current trends." Archives of Computational Methods in Engineering 29.7 (2022): 5397-5426.

[3] Nguyen, Thi-Ly, et al. "A novel integrating data envelopment analysis and spherical fuzzy MCDM approach for sustainable supplier selection in steel industry." Mathematics 10.11 (2022): 1897.

[4] Bou-Hamad, Imad, Abdel Latef Anouze, and Ibrahim H. Osman. "A cognitive analytics management framework to select input and output variables for data envelopment analysis modeling of performance efficiency of banks using random forest and entropy of information." Annals of Operations Research 308.1 (2022): 63-92.

[5] Mohammadnazari, Zahra, Amir Aghsami, and Masoud Rabbani. "A hybrid novel approach for evaluation of resiliency and sustainability in construction environment using data envelopment analysis, principal component analysis, and mathematical formulation." Environment, Development and Sustainability 25.5 (2023): 4453-4490.