Enhancing Pairs Trading with Adaptive Pair Rotation Strategies in Volatile Markets

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ABSTRACT

Pair trading strategies have long been utilized to capitalize on mispricing between correlated assets. However, traditional approaches often struggle to adapt to dynamic market conditions, resulting in suboptimal outcomes. In today's fast-paced financial markets, there is a growing need for strategies that deliver higher returns in shorter time frames. This paper presents an innovative adaptive pair rotation strategy that enhances financial decision-making through continuous evaluation and dynamic adjustments. The strategy is implemented in two stages: the first involves selecting stock pairs based on return-based correlation and ranking them by cointegration, and, the second applies adaptive methods to dynamically re-rank the pairs. By continuously adapting to market changes, the proposed approach ensures robustness and responsiveness in volatile financial environments. Empirical results demonstrate that this adaptive strategy yields more consistent and superior returns compared to traditional static methods, representing a significant advancement in trading strategies and financial engineering.

Keywords-pair trading; dynamic pair selection; adaptive pair rotation; financial market adaptability; market adaptation; cointegration ranking; returns maximization; volatile market

I. INTRODUCTION

Pair Trading Strategies (PTS) have been a staple in financial markets for decades, offering a market-neutral approach to capitalize on relative mispricings between two correlated assets [1, 2]. By simultaneously buying one asset and selling another, traders aim to profit from the convergence of their price movements. Traditionally, PTS relies on static stock pair selection, which involves choosing a set of pairs based on historical correlations and holding these stock pairs over a trading horizon [3-5]. However, the static nature of this approach often fails to account for the dynamic and ever-changing conditions of financial markets, resulting in suboptimal performance. The inherent challenge with traditional pair trading lies in its inability to adapt to shifting market dynamics. Market conditions are influenced by various factors, including economic indicators, geopolitical events, and investor sentiment, all of which can alter the correlations and price relationships between assets. As a result, pairs that once exhibited strong mean-reverting behavior may no longer do so, rendering static pair trading strategies less effective.

This paper proposes an enhancement to traditional PTS by incorporating dynamic pair selection through an Adaptive Pair Rotation Strategy (APRS). Unlike static pair selection, dynamic pair selection involves continuously evaluating and updating trading pairs based on market conditions. This adaptive approach allows the strategy to respond to emerging trends and shifting correlations, thereby enhancing its ability to capture profitable opportunities as they arise. The key innovation of APRS lies in its flexibility and responsiveness. The strategy maintains alignment with the prevailing market environment by systematically selecting and rotating pairs, enhancing its adaptability and resilience. This dynamic method maximizes returns and delivers more consistent performance across different market phases.

II. RELATED WORK

A literature review explored key advances in dynamic pair selection and pair rotation strategies in pair trading [1]. Since the first comprehensive analysis of this market-neutral strategy, various methods have emerged, including correlation, distance, cointegration, machine learning, and deep reinforcement learning [4-6]. The cointegration approach, particularly the Engle-Granger (EG) two-step method, revolutionized pair selection by identifying long-term equilibrium relationships between assets [7]. Comparative studies have analyzed cointegration versus distance-based selection, highlighting their strengths [8]. Traditional PTS relies on static selection methods, while studies have examined the effectiveness of Pearson's correlation for stock pair selection, paving the way for more adaptive trading strategies [9-11]. Recent advances have introduced the Dynamic Correlation Distance Measure (DCCT), which successfully captures lead-lag relationships and demonstrates superior performance compared to previous methods [12]. Additionally, the adoption of machine learning algorithms has been proposed to dynamically identify the most significant pairs, providing a more adaptive and resilient approach to PTS [4]. In [3], a high-frequency and dynamic pairs trading system was developed using a market-neutral statistical arbitrage strategy with a two-stage correlation and cointegration approach. High-Frequency Trading (HFT) was applied to equity trading, effectively identifying statistical mispricing between stock pairs and modeling them as mean-reverting processes with short holding periods. This approach demonstrated strong performance across varying market conditions in the US equities market.

The Dynamic Copula Method was proposed to eliminate the rigid assumptions implied by conventional approaches [10, 13]. These studies proposed optimal dynamic trading of cointegrated assets using the classical Mean-Variance (MV) portfolio selection criterion. This method was further advanced by incorporating optimal loss protection [14]. Subsequently, explicit optimal portfolio trading strategies were developed under the MV and expected utility frameworks [9, 15, 16]. Given the tractability and flexibility of the cointegration approach, this study adopts it as a foundational method for pair selection. A dynamic pair selection method with pair rotation is proposed to address the limitations of static pair selection, which struggles with market shifts. By continuously updating trading pairs using real-time data, statistical techniques, and machine learning, this approach ensures robust mean-reversion. The APRS trading model enhances flexibility and adaptability, making it more effective in evolving market conditions.

III. PROPOSED METHOD

The proposed APRS revolutionizes pair trading by continuously updating and rotating stock pairs based on market dynamics. Unlike static methods, it adapts to evolving conditions using historical correlations, cointegration, and trends to identify optimal pairs. The approach follows the key steps as explained in Table I.

A. Calculate the Daily Returns of the Stock

In the proposed approach, five stock files were randomly selected from a financial API (Yahoo Finance). The dataset includes features such as open, close, high, low, volume, and adjusted closing prices, with the latter used for predictions. Normalization using the min-max scaler ensures data consistency and proper scaling, a crucial step for maintaining uniformity [17, 18]. Let S be the set of m input stock files such that $S = \{s_1, s_2, \dots, s_m\}$. After normalizing and preprocessing the data, the daily returns for the stocks are calculated. The daily return, denoted $R_{s_i,t}$, is defined as the percentage change in the adjusted close price of the stock from one to the next day, and it is obtained as [19]:

$$R_{s_i,t} = \frac{P_{s_i,t} - P_{s_i,t-1}}{P_{s_i,t-1}}, \quad \text{for all } s_i \in S, \tag{1}$$

where $P_{s_i,t}$ is the adjusted closing price of the stock s_i at time t, and $P_{s_i,t-1}$ is the adjusted close price of the stock s_i at the previous time step $(t-1)$. For instance, if the adjusted closing price of stock s_i increases from $P_{s_i,t-1}$ to $P_{s_i,t}$, the daily return $R_{s_i,t}$ will be positive, indicating a gain. Conversely, if the price decreases, the return will be negative, indicating a loss.

TABLE I. PROPOSED METHOD FOR ADAPTIVE PAIRS TRADING STRATEGY WITH PAIR ROTATION

Steps	Description
Data acquisition	Collection of the historical stock price data.
Stock return calculation	Calculate daily returns from adjusted closing prices.
Optimized pair selection and ranking	Rank stock pairs using p-values.
Trading model	Apply an APRS for pairs trading.
Generate signals	Issue buy or sell signals based on predefined entry and exit criteria.
Metrics calculation and backtesting	Assess model performance with annual return metrics and validate through backtesting.

B. Optimized Pair Selection and Pair Ranking

Traditional pair selection uses adjusted closing prices to identify correlated stocks, whereas the optimized approach computes correlation based on stock returns, offering a clearer view of their relationships. The most correlated pair is selected and ranked using cointegration to ensure long-term stability. By focusing on returns, this method improves the accuracy of pair selection and enhances the effectiveness of trading strategies. The correlation coefficient $\gamma(s_i, s_j)$ quantifies the strength of the linear relationship between the daily returns of each stock pair (s_i, s_j), calculated as follows [12]:

$$\gamma(s_i, s_j) = \frac{\mathrm{Cov}(R_{s_i}, R_{s_j})}{\sigma_{R_{s_i}} \sigma_{R_{s_j}}} \tag{2}$$

for all $s_i, s_j \in S$ and $s_i \neq s_j$

where R_{s_i} and R_{s_j} denote the returns of stocks s_i and s_j, respectively, $\mathrm{Cov}(R_{s_i}, R_{s_j})$ represents their covariance, and $\sigma_{R_{s_i}}$ and $\sigma_{R_{s_j}}$ denote their standard deviations. A higher absolute value of $\gamma(s_i, s_j)$ indicates a stronger linear relationship between the daily returns of s_i and s_j. L denotes the list of correlated pairs obtained as follows:

$$L = \begin{cases} \text{if } \gamma(s_i, s_j) > 0, \text{ add to the correlated pair list,} \\ \text{otherwise, reject the pair.} \end{cases}$$

After identifying correlated pairs, cointegration testing ensures a stable long-term relationship, essential for pairs trading. The EG two-step test is used [1], first estimating regression between time series, then applying the ADF test on residuals for stationarity [20, 21]. This confirms cointegration, ensuring stable tradable pairs and optimizing trading opportunities. For each possible pair of stocks (s_i, s_j) in the set of correlated pairs $L = \{(s_1, s_2), (s_1, s_3), \dots, (s_i, s_j)\}$, where $(s_i, s_j) \in L$ and $i \neq j$, the EG procedure involves the following steps.

1) Regression Estimation

This step identifies the long-term relationship between the two series by estimating their linear association.

$$P_{s_j,t} = \alpha + \beta P_{s_i,t} + \epsilon_t \quad (3)$$

where $P_{s_j,t}$ is the adjusted closing price of a stock s_j at time t, $P_{s_i,t}$ is the adjusted close price of a stock s_i at time t, α and β are the intercept and slope coefficients, respectively, and ϵ_t is the residual (error term) of the regression.

2) Augmented Dickey-Fuller (ADF) Test

Applied to the residuals from the regression, the ADF test checks for stationarity. If the residuals ϵ_t are stationary, it suggests that deviations from the long-term relationship are temporary. The null hypothesis assumes that ϵ_t is non-stationary. Stationarity ensures that the time series lacks trends and has a constant mean and variance over time.

3) Cointegration Test

If the residuals are stationary, the two series are considered cointegrated, meaning they move together over time despite short-term fluctuations. If ϵ_t are stationary, s_i and s_j are cointegrate.

The EG test statistic τ is often calculated from the residuals, and its distribution is used to determine the significance of the cointegration. Let τ_{ij} denote the EG test statistic for the pair of stocks s_i and s_j:

$$\tau_{ij} = \frac{1}{T}\sum_{t=1}^{T} | \hat{\epsilon}_t |, \quad (4)$$

where the residuals $\hat{\epsilon}_t$ represent the deviations of the actual prices from the estimated long-term equilibrium relationship and T is the total number of observations. These are obtained through the following calculations:

$$\hat{\beta} = \frac{\sum_{t=1}^{T}(P_{s_i,t} - \bar{P}_{s_i})(P_{s_j,t} - \bar{P}_{s_j})}{\sum_{t=1}^{T}(P_{s_j,t} - \bar{P}_{s_j})^2}, \quad (5)$$

$$\hat{\alpha} = \bar{P}_{s_i} - \hat{\beta}\bar{P}_{s_j}, \quad (6)$$

$$\hat{\epsilon}_t = P_{s_i,t} - \hat{\alpha} - \hat{\beta}P_{s_j,t}, \quad (7)$$

where $\hat{\beta}$ is the slope of the regression line, representing the relationship between $P_{s_i,t}$ and $P_{s_j,t}$, $\bar{P}_{s_i}$ and $\bar{P}_{s_j}$ are the means of the adjusted close prices $P_{s_i,t}$ and $P_{s_j,t}$, respectively, and $\hat{\alpha}$ is the intercept of the regression line, adjusting for the average prices of $P_{s_i,t}$ and $P_{s_j,t}$. The τ_{ij} statistic helps to quantify the extent of deviations from the equilibrium relationship between s_i and s_j. Lower values of τ suggest a stronger cointegration, indicating that the residuals are small and the relationship is stable over time. The p-value measure is used as a probability value that measures the strength of evidence against the null hypothesis in a statistical hypothesis test. The selection criterion using the p-value between the s_i and s_j can be expressed as:

$$\left(p\text{-value}_{ij} < 0.05\right) \Rightarrow \left(s_i, s_j\right) \in \mathcal{L}.$$

The set $\mathcal{L}$ contains all selected cointegrated pairs identified using the Engle-Granger test with a significance threshold of 0.05. Lower p-values indicate stronger evidence of cointegration, suggesting a stable long-term relationship between stocks (s_i, s_j). By iteratively applying the test across all pairs, the cointegrated ones are stored in $\mathcal{L}$. These pairs are then ranked based on their p-values in ascending order, forming the ranked set $\mathcal{R}$, where rank 1 is assigned to the pair with the lowest p-value. This ranking prioritizes pairs with the strongest cointegration.

C. APRS Trading Model

The strategy starts by selecting the top-ranked stock pair from the set $\mathcal{R}$, denoted as (s_i, s_j). The strategy relies on spread, moving averages, and Z-scores to generate trading signals based on deviations from historical trends. The spread, δ_t is defined as the difference between the daily returns of stocks s_i and s_j at time t and is calculated as [21]:

$$\delta_t = R_{s_i,t} - R_{s_j,t}, \quad (8)$$

where $R_{s_i,t}$ and $R_{s_j,t}$ are the daily returns of stock s_i and s_j at time t, respectively. The moving average μ_t of the spread between stocks s_i and s_j over a specified window of n days is calculated as [13]:

$$\mu_t = \frac{1}{n}\sum_{t'=t-n+1}^{t} \delta_{t'}, \quad (9)$$

where $\delta_{t'}$ denotes the spread between the daily returns of stocks s_i and s_j at day t', and t' is an index variable representing each time step within the window. The z-score Z_t on the t^{th} the day is calculated by using δ_t and μ_t as [12]:

$$Z_t = \frac{\delta_t - \mu_t}{\sigma}, \quad (10)$$

where σ is the standard deviation of the spread over the same window of n days. The pair rotation strategy identifies trading opportunities by analyzing Z-score deviations and moving averages of the top-ranked pair. It exploits mean reversion by trading on temporary spread divergences, aiming for profits as spreads normalize. Excluding an initial window, it systematically evaluates multiple pairs over time, triggering entries when the Z-score exceeds the threshold and exits when it falls below. Continuous reranking enables the strategy to adapt to changing market conditions, enhancing its responsiveness and effectiveness.

- Input: Set of initially ranked pairs $\mathcal{R} = \{(s_1, s_2), (s_3, s_4), \dots, (s_i, s_j)\}$, $i, j = 0,1,2 \dots, n$, price data $P_{s_i,t}$ for all stocks, entry threshold $Entry_\theta = 1.0$, exit threshold, $Exit_\theta = 0.5$.
- Initialize: current_pair_index ← 0 , active_pairs ← ∅

- Select the highest-ranked pair:
  - CurrentPair ← $\mathcal{R}$[current_pair_index] $= (s_i, s_j)$
  - Add CurrentPair to active_pairs
  - Calculate δ_t, μ_t and Z_t for CurrentPair
  - Enter the trade - Exit the trade
  - Remove CurrentPair from active_pairs
- After exit, re-rank all pairs:
  - Recalculate the p-value p_{ij} Sort pairs in $\mathcal{R}$ in ascending order of p_{ij}
  - Reset current_pair_index ← 0
- Update trading results: Log trading actions, entry and exit points, and output buy/sell trading results.

D. Evaluation Metrics

The evaluation of the trading strategy involves several key metrics that assess its performance over time. The strategy review hinges on robust assessments of yearly (R_y) and monthly returns (R_m) calculated as [16]:

$$R_m = \sum_{t \in \text{month}} \text{Position}_{s_i,t} \times (R_{s_i,t} - R_{s_j,t}), \quad (11)$$

$$R_y = \sum_{t \in \text{year}} \text{Position}_{s_i,t} \times (R_{s_i,t} - R_{s_j,t}) \quad (12)$$

where $\text{Position}_{s_i,t}$ represents the position (1 for long, -1 for short, 0 for neutral) of stock s_i on day t, and $R_{s_i,t}$ and $R_{s_j,t}$ denote the daily returns of stocks s_i and s_j, respectively. Another evaluation metric used is cumulative returns (R_c), which offers a strategy's overall profitability throughout the investment period, expressed as [19]:

$$R_c = \sum_{m=1}^{M} R_m \quad \text{(Monthly)}$$

$$R_c = \sum_{y=1}^{Y} R_y \quad \text{(Yearly)} \quad (13)$$

This metric provides an aggregated measure of the strategy's profitability over the entire investment horizon. Moreover, key performance metrics such as maximum drawdown, $DD_{\max}$ ($\Delta_{\max}$), and the win ratio ω further enhance the evaluation process, given by [14, 21]:

$$\Delta_{\max} = \min\left(\frac{R_c}{R_{c,\max}} - 1\right), \quad (14)$$

$$\omega = \frac{\text{Number of Positive Trades}}{\text{Total Number of Trades}}, \quad (15)$$

where $R_{c,\max}$ denotes the maximum value of cumulative returns over the evaluated period. Here, positive trades represent the count of profitable trades, while the total trades include all executed trades, regardless of outcome. Together, they assess both the profitability and effectiveness of risk management.

IV. RESULTS AND DISCUSSION

The experiments applied various algorithms to implement the APRS trading model using randomly selected NASDAQ stocks from the Yahoo Finance API (Jan 1 - Dec 1, 2023). The data was preprocessed and scaled using min-max normalization, and daily returns were calculated based on adjusted closing prices. The most correlated stock pairs were identified using Pearson correlation, and the EG cointegration test was applied to ensure a stable long-term relationship among the pairs. These pairs were ranked by their p-values, with lower p-values indicating stronger cointegration. Out of 199 trading days (after excluding a 30-day window), the top 10 correlated and cointegrated pairs were compiled, with AMZN-MSFT emerging as the strongest pair, displaying a high correlation of 0.5729 and an extremely low p-value of 1.25×10^{-28}. This pair was selected as the initial candidate for the proposed adaptive trading strategy.

TABLE II. RANKED CORRELATED AND COINTEGRATED PAIRS

Stock Pair	Correlation	P-value	Rank
AAPL-AMZN	0.4408	4.3538e-24	8
AAPL-GOOGL	0.5438	3.2666e-24	7
AAPL-MSFT	0.5544	2.3891e-25	5
AAPL-TSLA	0.4464	6.1931e-26	3
AMZN-GOOGL	0.6029	5.5492e-28	2
AMZN-MSFT	0.5729	1.2500e-28	1
AMZN-TSLA	0.3773	1.0158e-22	10
GOOGL-MSFT	0.5162	2.0073e-25	4
GOOGL-TSLA	0.3467	2.4732e-25	6
MSFT-TSLA	0.3278	4.3792e-24	9

Once the pairs were ranked, the APRS trading strategy selected the rank 1 pair (AMZN-MSFT) for trading and checked the Z-score conditions to determine the trading actions, such as which stock to buy and which to sell. When an exit signal is triggered (Z_t < Exit_θ), the trade is closed, and the reranking process is performed again, marking the completion of rotation one. This process continues in the same manner for subsequent entry and exit actions.

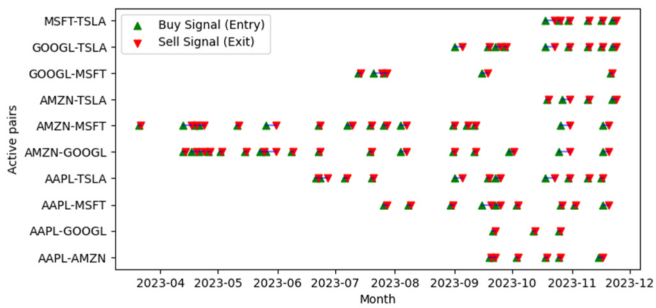

Fig. 1. Visualization of buy and sell signals for active stock pairs using the APRS trading model over time.

To determine the optimal window size for APRS, both annual returns and rotation frequency must be considered. Higher returns indicate greater profitability, while fewer rotations help minimize transaction costs. However, the ideal rotation frequency depends on the strategy's trading tolerance. Balancing these factors is key to maximizing performance. The proposed approach evaluates different window sizes by analyzing their impact on annual returns and rotations. Figure 2 visualizes this relationship, highlighting the most effective window size for APRS. A 30-day rolling window delivers the best performance for APRS, achieving 479.12% annual returns across 86 rotations. This window size effectively captures spread dynamics between stock pairs. Figure 2 compares month-wise cumulative returns of traditional PTS and APRS, highlighting APRS's superior adaptability and profitability throughout the trading period.

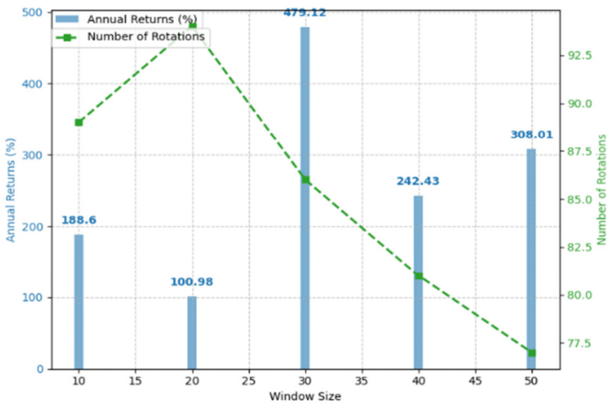

Fig. 2. Comparative analysis of annual returns and number of rotations across different window sizes for optimal selection in the APRS trading model.

The APRS algorithm conducted 86 pair rotations throughout the trading period, dynamically adjusting to market changes. Table III presents 10 representative rotations, listing top-ranked stock pairs with their corresponding correlation coefficients and p-values, illustrating the model's ability to prioritize pairs with strong statistical relationships.

TABLE III. ROTATION-WISE SELECTED PAIRS WITH CORRELATION, P-VALUE, AND RANK

Rotation	Selected Pair	Correlation	P-value	Rank
1	AMZN-MSFT	0.572935	1.249959e-28	1
2	AMZN-GOOGL	0.602880	5.549193e-28	1
3	AAPL-TSLA	0.446365	6.192602e-26	1
4	GOOGL-MSFT	0.516227	2.007361e-25	1
5	AAPL-MSFT	0.554412	2.388897e-25	1
6	GOOGL-TSLA	0.346720	2.473186e-25	1
7	AAPL-GOOGL	0.543769	3.266472e-24	1
8	AAPL-AMZN	0.440806	4.353518e-24	1
9	MSFT-TSLA	0.327808	4.379314e-24	1
10	AMZN-TSLA	0.377322	1.015813e-22	1

Table IV summarizes monthly rotation activity, capturing both the frequency of pair switches and the duration of active pairs. Notably, March 2023 involved a single rotation with AMZN-MSFT held for 36 days, while October 2023 experienced increased volatility with 18 rotations and MSFT-TSLA active for only 11 days. These variations reflect the adaptive nature of APRS in responding to fluctuating market conditions.

Figure 3 presents month-wise cumulative returns of traditional PTS and APRS, showcasing APRS's improved performance, profitability, and adaptability over time.

TABLE IV. MONTH-WISE NUMBER OF ROTATIONS AND ACTIVE PAIRS WITH THE NUMBER OF ACTIVE DAYS.

Monthly rotations		Active pairs	
Month	Number of rotations	Stock pair	Number of active days
Mar-2023	1	AMZN-MSFT	36
Apr-2023	7	AMZN-GOOGL	37
May-2023	6	AAPL-TSLA	23
Jun-2023	5	GOOGL-MSFT	11
Jul-2023	10	AAPL-MSFT	18
Aug-2023	6	AAPL-GOOGL	3
Sep-2023	17	AAPL-AMZN	7
Oct-2023	18	MSFT-TSLA	11
Nov-2023	16	AMZN-TSLA	8

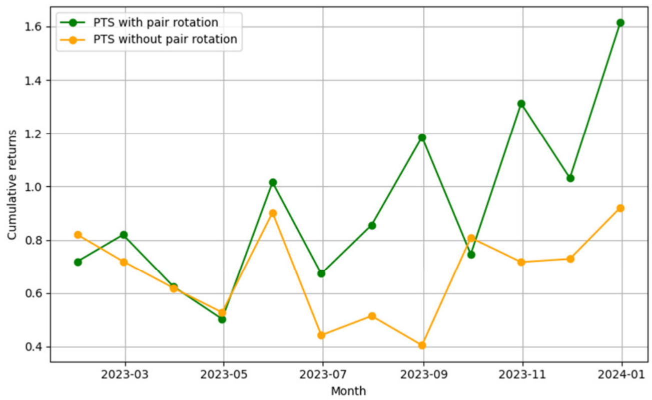

Fig. 3. Monthwise cumulative returns of the traditional PTS and APRS.

The APRS trading model demonstrates strong performance by achieving the highest win ratio (0.62), outperforming HFT with Dynamic PTS (0.58) and Traditional PTS (0.52), while maintaining a maximum drawdown of 0.00, indicating effective risk control. To assess its robustness, APRS was evaluated against several established algorithms, including Random Forest (RFA), ADF, and the EG cointegration test. As illustrated in Figure 4, the comparative analysis includes five pair trading strategies: Traditional PTS, APRS with RFA, APRS with ADF, APRS with EG, and HFT with Dynamic PTS. Among these, APRS achieved the highest overall return (705.61%), underscoring its effectiveness in optimizing trading performance and offering valuable insights for strategy development.

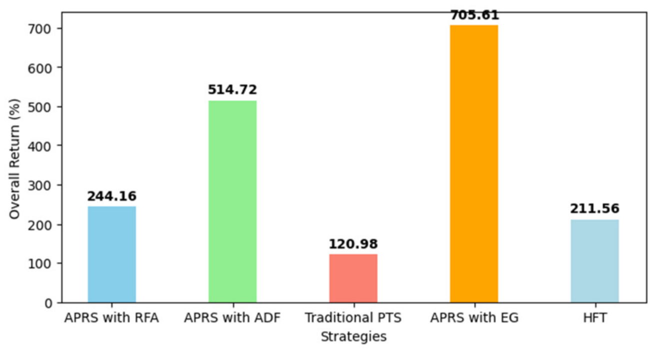

Fig. 4. Comparison of overall returns across different PTS strategies.

The backtesting results further validate the practical utility of the model. Beginning with a virtual portfolio of $100,000, APRS grew the capital to $110,166.66 before transaction costs and $110,056.49 after fees, reflecting minimal slippage and transaction impact. Furthermore, APRS consistently outperformed benchmark models in cumulative monthly returns, highlighting both its adaptability to varying market conditions and its superiority as a dynamic, data-driven trading approach.

V. CONCLUSION

The proposed APRS provides a dynamic and flexible framework for pairs trading by leveraging correlation and cointegration to select optimal stock pairs. This method outperformed traditional static methods by achieving higher returns, better market adaptability, and strong risk control. APRS recorded the highest win ratio (0.62), surpassing HFT with Dynamic PTS (0.58) and Traditional PTS (0.52) while maintaining a zero Maximum Drawdown. The proposed APRS was benchmarked against multiple models, including RFA, ADF, and EG tests, in five trading strategies, and achieved the highest overall return of 705.61%, underscoring its superiority in trading performance. Although the model improves both short-term gains and long-term stability, managing larger stock pools increases computational demands. Future work will focus on scaling efficiency using dimensionality reduction, parallel computing, and reinforcement learning. Incorporating deep learning models and hybrid data will further refine decision-making and personalization for diverse market conditions.

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