

Training Knowledge Transfer for Adaptive Portfolio Rebalancing Based on Trend Ratio with Quantum-inspired Optimization System

Short Paper

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Abstract

This study presents a unified investment decision framework delivered via quantum computing-as-a-service (QCaaS), integrating stock selection and market timing for dynamic portfolio rebalancing. A quantum-inspired optimization (QIO) algorithm, GNQTS, is employed to construct stable uptrend portfolios based on the trend ratio. To address the limitations of fixed-length sliding windows in volatile markets, an adaptive sliding window (ASW) mechanism is proposed. The ASW dynamically adjusts rebalancing timing using quadratic regression monitoring of portfolio trends, enabling timely responses to market reversals. Experimental results on DJIA data (2012–2021), covering volatile and extreme conditions such as the Covid-19 period, demonstrate that the QIO-based ASW consistently outperforms the classical sliding window, achieving superior return-to-risk performance. This work advances the application of QIO in cloud-based financial decision systems and highlights the role of adaptive timing strategies in enhancing robustness under non-stationary market conditions.

Keywords: Quantum Computing-as-a-service, Quantum-inspired Optimization, Adaptive Sliding Window, Quadratic Regression, Portfolio Optimization, Market Timing

Introduction

Quantum computing has emerged as a new paradigm for solving complex problems that classical computers struggle to handle. However, the current noisy intermediate-scale quantum (NISQ) era still faces several critical challenges before widespread adoption, such as the lack of fault-tolerant computation and significant noise and errors. Against this backdrop, bridging classical computing with quantum principles to realize partial quantum advantage becomes increasingly important, especially in domains such as finance. Quantum-inspired optimization (QIO) simulates quantum behaviors to navigate large and nonlinear search spaces effectively (Hakemi et al., 2024; Montiel et al., 2019). This emerging technology is advancing rapidly, and QIO techniques can now be deployed as cloud services to meet the high demand for business applications and improve accessibility.

In financial applications, especially in the stock market, decision-making requires both accuracy and responsiveness under uncertainty (Shi et al., 2021). In this context, two core components of successful stock market strategies—stock selection and market timing—pose significant challenges due to the abundance of financial instruments and frequent trading signals, which create a dynamic and complex environment,

making optimization easily gets trapped into local optima. The built-in amplitude probability model makes QIO a well-suited technique to address these challenges by handling complex financial optimization problems in uncertain and high-dimensional spaces. However, financial data are inherently time-sensitive. The classical sliding window (SW) approach (Selvin et al., 2017), which is widely adopted to update fresh data across training and testing periods, segments historical data in each window, enabling portfolio optimization on the most recent observations (i.e., training period) and performance evaluation on out-of-sample data (i.e., testing period). However, this rigid execution timing, restricted to the beginning and end of each window, lacks the agility to respond to real-time market fluctuations, potentially leading to missed opportunities for profitable entries or exits. To address this limitation, the proposed unified system introduces a data-driven adaptive sliding window (ASW) mechanism integrated with a regression model to dynamically adjust window length based on market volatility, trend continuation, and portfolio performance feedback.

This study develops a comprehensive decision-making framework that unifies stock selection and market timing, delivered through quantum computing-as-a-service (QCaaS) in a scalable cloud-based architecture. The system is structured into three interrelated periods, each serving a distinct role in supporting timely investment decisions under changing market conditions:

(1) Training Period: The QCaaS applies a QIO technique to business and financial data to optimize portfolio performance, aiming to construct a portfolio that demonstrates a stable upward trend, as evaluated by the trend ratio (TR).

(2) Validation Period: This phase is the core innovation of the proposed ASW mechanism. It continuously monitors portfolio performance using quadratic regression to determine whether the current investment should be terminated. A trading signal is triggered when the upward trend weakens or reverses, prompting portfolio re-optimization.

(3) Testing Period: This phase evaluates the performance of different ASW configurations using a new metric—the annualized emotion index (AEI), which more fairly reflects volatility by capturing annual fluctuations instead of full-period deviations.

A key contribution is the validation-phase monitoring mechanism, which leverages training knowledge to track quadratic trends during the testing period. This enables the ASW framework to respond to market fluctuations rather than relying on fixed timing rules. By linking trading decisions directly to the monitored performance of the selected portfolio, the system forms a unified and mutually supportive investment strategy, demonstrating that QIO can be effectively integrated into cloud-based financial decision systems.

Literature Review

This study addresses the challenge of constructing a unified investment decision system, in which portfolio construction (stock selection) forms the foundational layer. The effectiveness of market timing heavily depends on the robustness of the selected portfolio. Therefore, identifying high-quality stock combinations that exhibit stable upward trends is a prerequisite for subsequent monitoring and rebalancing. Given the vast solution space of possible portfolio combinations, evolutionary computation (EC) has been widely adopted to solve high-complexity optimization problems by rapidly converging to near-optimal solutions. Due to its ability to handle complex, dynamic, and nonlinear problems, EC techniques are frequently applied in the financial applications (Brabazon et al., 2008). Among them, the genetic algorithm (GA) (Holland, 1992), one of the most well-known EC techniques, has been frequently adopted in portfolio optimization tasks (Chen et al., 2019; Cheong et al., 2017; Fernandez et al., 2020; Skolpadungke et al., 2007). However, according to the no free lunch (NFL) theorem (Wolpert & Macready, 1997), no single algorithm is universally superior across all problem domains, prompting researchers to explore alternative approaches tailored to the complexities of financial data (Ponsich et al., 2013; Cura, 2009; Yu et al., 2016).

Quantum-inspired optimization (QIO) has recently gained attention as a promising class of algorithms capable of addressing high-dimensional, nonlinear, and non-stationary financial applications. Classical methods often suffer from premature convergence and require extensive parameter tuning, which limits their adaptability in volatile markets. While operating on classical hardware, QIO quantum phenomena—such as superposition and amplitude probability—to enhance global search capability and avoid premature convergence. A recent study by Jiang et al. (2023) applies QIO to international portfolio optimization,

leveraging an entanglement local search approach through the global best-guided quantum-inspired tabu search algorithm with a quantum-not gate (GNQTS) to reduce stagnation and demonstrating its superiority over GA in financial applications. Building on these findings, this study adopts GNQTS as the optimization engine to generate candidate portfolios with stable upward trends and integrate adaptive trading timing mechanism along with the portfolio optimization.

Beyond the optimization technique itself, the temporal structure of financial data plays a critical role in investment performance. To simulate practical investment cycles, many studies use the sliding window (SW) framework to divide historical data into training and evaluation periods (Selvin et al., 2017; Yuan et al., 2020). However, the majority implementations rely on fixed-length windows, which may lack the flexibility to accommodate abrupt market fluctuations or trend reversals. The introduction of the adaptive-length concept is an emerging topic, and prior studies (Prakash et al., 2021; Wang & Hsieh, 2022) have dynamically determined the size of the next trading window. However, such approaches cannot respond to sudden events occurring within the current trading period. To improve adaptability under volatile conditions, this paper proposes an ASW that adjusts rebalancing timing within the current window based on portfolio trend changes. A validation phase monitors trend continuity via regression, triggering re-optimization when a reversal is detected. By leveraging training knowledge and adapting to real-time signals, ASW improves responsiveness under market volatility.

Adaptive Sliding Window in Optimizing Portfolio Rebalancing

This study presents the quantum-inspired intelligent decision optimization system integrated with QCaaS, featuring an adaptive sliding window mechanism for dynamic rebalancing. First, the overall structure of the intelligent system is introduced. Then, the essential components for implementation—trend ratio evaluation, quantum-inspired optimization technique, adaptive sliding window, and annualized emotion index—are detailed to highlight their roles in the system's contribution.

Overall Intelligent Trading System Schematic

While stock selection and trading timing are often treated as independent tasks in the literature, this study integrates them into a unified and mutually supportive decision-making framework. Figure 1 presents the overall architecture of the proposed ASW system, which incorporates QCaaS to address portfolio optimization and trading timing. In stock investment, responsiveness to market fluctuations is critical. To maintain fresh data, the SW technique is employed, as illustrated in Figure 2(a). Unlike fixed-interval rebalancing, the proposed ASW dynamically adjusts trading decisions in response to real-time market feedback, as shown in Figure 2(b). During the validation period, the system monitors the performance of the selected portfolio on unseen data using insights derived from the training phase. A trading signal is triggered based on a quadratic trend regression threshold. When the trend weakens, the system initiates portfolio rebalancing. A new training period then begins, producing a refreshed optimal portfolio for subsequent investment. The following section details the methodology, structured around the three ASW phases: training, validation, and testing.

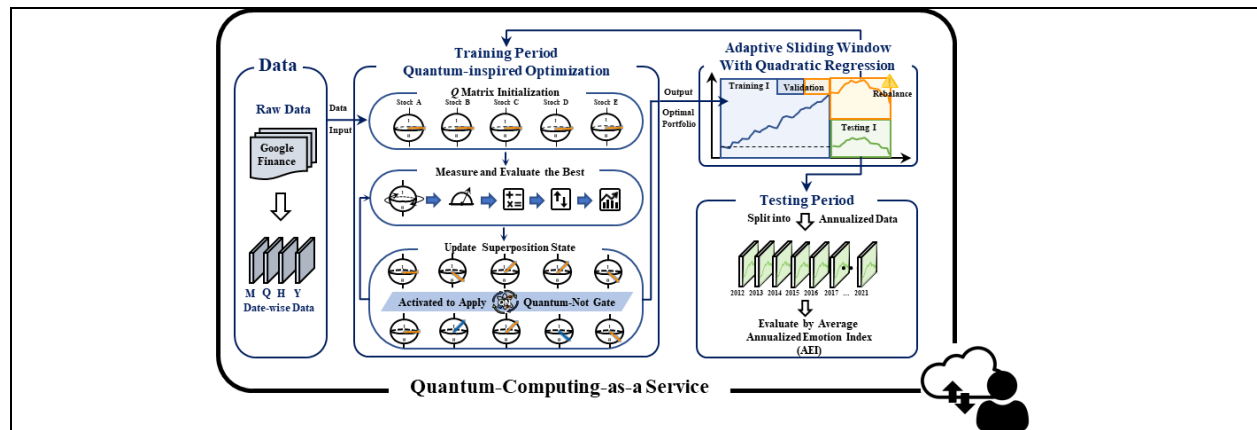


Figure 1. Architecture of the proposed ASW system with QCaaS for decision-making. In the data flow from left to right, the training period uses time-series data of varying lengths

to build an optimal portfolio via QIO. The validation period applies quadratic regression to monitor trend changes, triggering the testing period when a downtrend is detected. Finally, the testing phase computes AEI from annualized data to evaluate performance.

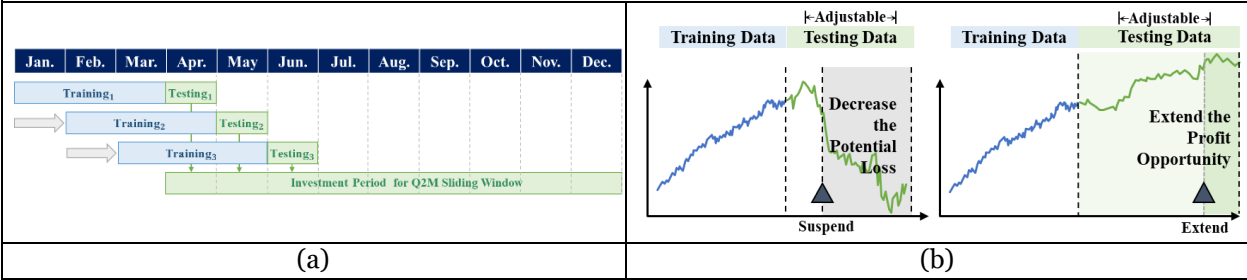


Figure 2. (a) A classical fixed-length sliding window framework, consisting of three months of training followed by one month of testing. After the first testing period, the window is shifted forward by one month, and the second testing period is preceded by the most recent three-month training segment. (b) The testing period in ASW is dynamically adjusted based on trading signals derived from regression monitoring, allowing the system to mitigate potential losses or extend profit opportunities.

Training Period

Portfolio Evaluation Model—Trend Ratio Regression Model

The trend ratio (TR) (Chou et al., 2019) is a regression-based technical indicator designed to evaluate a portfolio's risk-return profile. This model assesses performance by consolidating multiple stock price trajectories into standardized funds representation. This standardization process transforms the portfolio into a single composite curve that captures interactions among constituent stocks. A linear regression is then applied to the composite curve, where the slope represents the expected daily return (i.e., the portfolio's growth trend) while the residuals quantify the volatility or risk. A stable upward trend corresponds to a high return with low residuals, indicating desirable low-risk behavior. The TR is formulated as the ratio of expected return to residual risk, effectively favoring portfolios with strong and consistent upward momentum. This evaluation anticipates a sustained, stable uptrend and is used as the core metric for selecting optimal portfolios in the training period.

Quantum-inspired Optimization Technique within the QCaaS

In the QIO technique, quantum superposition serves as the core principle for representing stock selection status. Each stock is modeled as a qubit in superposition, as defined in Equation (1), where the amplitude of state $|1\rangle$ indicates inclusion in a portfolio, and $|0\rangle$ indicates exclusion. A Q -matrix is maintained to record the superposition status (β) of each stock and is iteratively updated throughout the optimization process.

GNQTS is a powerful QIO algorithm that outperforms classical computational intelligence techniques, particularly in fast-changing financial environments. Its main idea is to converge efficiently toward the best solution while simultaneously avoiding poor ones. The main steps—measurement, evaluation, and update with the quantum-not (QN) gate—are outlined in Algorithm 1.

GNQTS generates candidate populations P by measuring the superposition states in the Q -matrix. Each portfolio is then evaluated using the trend ratio, which balances return and risk. Based on these evaluations, the global best solution (Gb) and the local worst (Lw) solution are identified. To guide convergence, GNQTS applies a QN gate, which is defined in Equation (2), to reverse amplitude directions when the Q -matrix is biased toward poor solutions, helping the algorithm escape local optima. Finally, the Q -matrix is updated using information from both Gb and Lw portfolios, with a rotation angle θ that controls the degree of convergence. The mechanism of moving toward Gb and away from Lw allows GNQTS to maintain a balance between exploration and exploitation, achieving superior performance in portfolio optimization tasks.

$$|\psi_i\rangle = \alpha_i|0\rangle + \beta_i|1\rangle, \text{ where } \|\alpha_i\|^2 + \|\beta_i\|^2 = 1 \quad (1)$$

$$QN(|\psi_i\rangle) = QN(\alpha_i|0\rangle + \beta_i|1\rangle) = \beta_i|0\rangle + \alpha_i|1\rangle \quad (2)$$

Algorithm 1: GNQTS Algorithm

```

Input: Target Segment Stock Price
/* Step 1: Initialization */
1 Initialize  $Q$  to Record the  $\beta$  State in a Superposition;
2 while stopping condition is not met do
    /* Step 2: Measurement */
    3 Generate Quantum Populations  $P$  by Measuring  $Q$ 
    /* Step 3: Fitness Evaluation */
    4 Calculate the Fitness of Each Population  $p_i \in P$ 
    5 Sort  $P$  Based on Fitness
    6 Identify  $Gb \leftarrow$  Global Best Solution
    7 Identify  $Lw \leftarrow$  Local Worst Solution
    /* Step 4: Quantum-Not Gate */
    8 Check the Coherence Between  $Q$  Bias and  $Gb$ 
    /* Step 5: Global Best Update */
    9 Update  $Q$  with Status of  $Gb$  and  $Lw$  by a  $\theta$ 
10 end
11 Output: Global Best Solution  $Gb$ 

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Validation Period

Once the optimal portfolio is identified, the testing period serves as the investment phase, where the trained portfolio is evaluated on unseen data in a non-stationary environment. Although the price data remains continuous between the training and testing periods, ensuring that recent data informs investment decisions, the fund levels cannot be directly carried over from the end of the training to the start of the testing. To bridge this gap, a validation period is introduced to extend the fund trajectory from training, enabling continuous trend monitoring in a non-stationary market.

During the training period, linear regression (LR) is used to construct a steadily uptrending portfolio. In contrast, the validation phase applies quadratic regression (QR) to capture trend variations across both training and testing data. Compared to LR, QR offers greater flexibility and predictive power by increasing the degree of freedom (Kuo *et al.*, 2019), enabling it to detect gradual declines and respond to turning points more effectively than a linear model. This study uses the most recent tangent slope of the QR curve to determine trend reversals, thereby avoiding the overfitting risk and higher computational demands associated with higher-order nonlinear models. When the slope turns negative, a stop signal is triggered, ending the current testing segment and prompting portfolio rebalancing.

Since the validation period encompasses both the training and testing periods, the balance of data usage is a critical factor. After QIO converges to the best trend ratio portfolio during training, the portfolio typically follows a stable linear uptrend. If training data dominates, QR trends tend to be more stable and less reactive to new, unseen data, allowing for higher risk endurance by filtering out minor fluctuations. Conversely, if the validation period consists mostly of testing data, QR becomes more flexible and sensitive to recent changes, but with increased volatility in observed trends.

To address this trade-off, two validation window designs are considered: gradual expanding (GE) and dynamic sliding (DS). In the classical sliding window, the testing period is typically shorter than the training period. Accordingly, two GE variants are examined: less-than-training (LTT), which restricts testing length, and no limitation (NL), which removes this constraint. These configurations offer broader flexibility in adapting to market conditions. Thus, ASW observation supports three mechanisms: GE-LTT, GE-NL, and DS-NL. The configurations are illustrated in Figure 3. Equation (3)–(5) define the QR line, where x_i is the i th day; c is the initial funds; a and b are the coefficients; Y_i is the expected funds standardization of i th day; and y_i is the actual funds standardization of i th day.

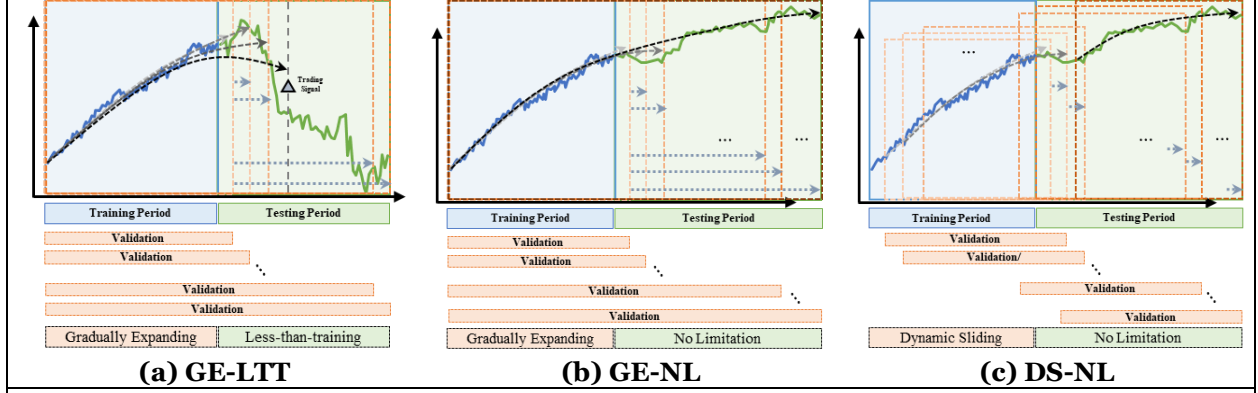


Figure 3. Three quadratic regression methods focus on pattern variation. (a) GE-LTT: The validating period gradually expands, and the testing length is less than the training. (b) GE-NL: The validating period gradually expands, and the testing length has no limitations. (c) DS-NL: The validating period is dynamically sliding but not increasing in length, and the testing length has no limitations.

$$Y_i = ax_i^2 + bx_i + c \quad (3)$$

$$\begin{bmatrix} x_1^2 & x_1 \\ \vdots & \vdots \\ x_i^2 & x_i \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} y_1 - c \\ \vdots \\ y_i - c \end{bmatrix} \quad (4)$$

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(\begin{bmatrix} x_1^2 & x_1 \\ \vdots & \vdots \\ x_i^2 & x_i \end{bmatrix}^T \begin{bmatrix} x_1^2 & x_1 \\ \vdots & \vdots \\ x_i^2 & x_i \end{bmatrix} \right)^{-1} \begin{bmatrix} x_1^2 & x_1 \\ \vdots & \vdots \\ x_i^2 & x_i \end{bmatrix}^T \begin{bmatrix} y_1 - c \\ \vdots \\ y_i - c \end{bmatrix} \quad (5)$$

Testing Period

Since actual returns are observed in the testing period, risk is assessed based on realized volatility rather than predicted trends. To achieve this, the emotion index (EI) (Chou *et al.*, 2022) is adopted to evaluate portfolio performance. EI shares a similar concept with the trend ratio, as both measure return per unit of emotional fluctuation. EI considers daily profits from the first to the last day of the testing period, while treating fluctuations between funds standardization (FS) and the first-to-last (FL) line as risk, as illustrated in Figure 4(a). The equations for calculating the EI are provided in Equations (6)–(9), where D represents the total number of days in the period.

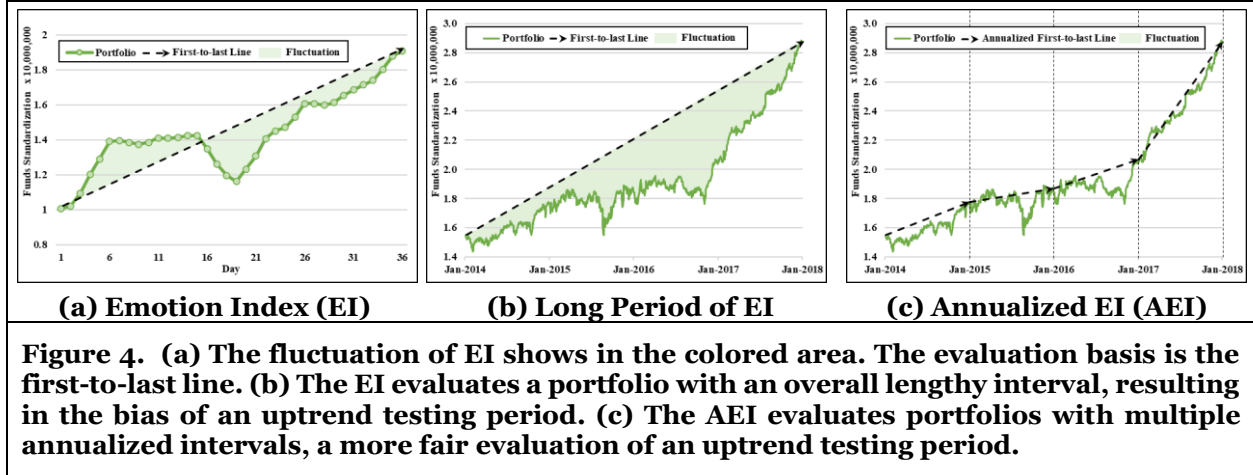
EI is a reasonable metric for evaluating performance during the testing period. However, over long investment horizons, strongly trending portfolios may be misclassified as high-risk. This misinterpretation stems from the FL line, which only connects the start and end points. As shown in Figure 4(b), the portfolio from 2014 to 2018 demonstrates a strong upward trend, yet its deviation from the FL line appears large, introducing potential bias. Consequently, variations in testing length can lead to inconsistent performance assessments. To address this issue, the annualized EI (AEI) is proposed. AEI evaluates returns over one-year intervals, following the standard annualized approach. The investment period is split into yearly segments, each with its own FL line, as shown in Figure 4(c). AEI is computed for each year, and the final score is the average across years, enabling consistent and fair comparisons regardless of investment length.

$$\text{Daily Profit} = \frac{FS_D - FS_1}{D - 1} \quad (6)$$

$$FL_i = \text{Daily Profit} \cdot (i - 1) + FS_1 \quad (7)$$

$$\text{Daily Fluctuation} = \sqrt{\frac{\sum_{i=1}^D (FL_i - FS_i)^2}{D}} \quad (8)$$

$$\text{Emotion Index} = \frac{\text{Daily Profit}}{\text{Daily Fluctuation}} \quad (9)$$



Experiment Results

This study evaluates a QIO-based ASW mechanism that monitors an optimized uptrend portfolio and applies dynamic rebalancing in response to market fluctuations. Three ASW configurations are introduced to manage the validation period and determine retraining timing. Experiments assess each phase of the framework: GNQTS is compared with exhaustive search in training; different ASW configurations for the validation phase are evaluated using testing-period AEI, enabling comparison of validation strategies under dynamic market conditions. The ASW configurations are further compared under varying training lengths—M (22 days), Q (65 days), H (125 days), and Y (250 days)—alongside the classical SW approach.

Experimental Environment

The investment target comprises the constituent stocks of the Dow Jones Industrial Average (DJIA), with price data retrieved from Google Finance, covering the period from January 2012 to December 2021. This time span is representative as it includes the pre-, mid-, and post-Covid-19 periods, which have been reported as highly volatile and extreme conditions (Izzeldin et al., 2021), thereby allowing the robustness of the ASW to be examined. During training, portfolios are optimized using the GNQTS algorithm based on trend ratio evaluation. The parameters follow Chou et al. (2021), which was conducted under the DJIA environment using GNQTS: 50 independent runs, 10 particles, 10,000 generations, and a rotation angle of 0.0004. The initial fund is set to 10 million USD, and capital is equally allocated across selected stocks. If the portfolio performs negatively in a given window, no investment is made. Experiments were implemented in C++ on a PC with an Intel i3-10100 CPU (3.6 GHz) and 8 GB RAM.

Training Period Technique Comparison

The previous section demonstrated the effectiveness of GNQTS over its predecessor techniques. To further validate solution quality, GNQTS is benchmarked against an exhaustive search on the 30 DJIA components using binary decision variable, resulting in a $2^{30} = 1,073,741,824$ combinations. Table I presents a comparison of the exhaustive method and GNQTS across ten years training periods. Despite exploring only 0.47% of the full search space, GNQTS consistently identifies the same optimal solution while reducing runtime by 99.71%. These findings confirm that GNQTS is a highly efficient and effective algorithm for achieving the optimal solution with significant reduction in computational cost.

Optimized Method	Exhaustion	GNQTS
Computational Complexity	1,073,741,824	5,000,000
Proportion	-	0.47%
Computational Times (s)	143,660.4	421.8
Improvement	-	99.71%
Trend Ratio	0.0637	0.0637

Table I. Comparison of GNQTS and exhaustion method

Validation Period Technique Performance Analysis of Adaptive Sliding Window

This section examines the performance of ASW methods in the validation period by comparing the AEI values in the testing period. The three proposed ASW methods differ in training length settings due to conceptual differences. The QR mechanism considers four training lengths: M, Q, H, and Y. Due to the different balances of training and testing data used in the three ASW-QR configurations, their testing performance is evaluated to highlight their respective advantages. Table II presents the AEI comparison among the three methods and the classical SW approach. The results consistently demonstrate that training-H yields the highest average AEI across all methods, outperforming Q, M, and Y. Among the three QR configurations, GE-LTT achieves the highest AEI, suggesting that a trend ratio-evaluated portfolio has strong potential to deliver stable performance in a non-stationary market. Figure 5 depicts the portfolio trends of GE-LTT, GE-NL, DS-NL, and the classical SW method under the best-performing training-H setting. Among these, GE-NL achieves the highest return, while GE-LTT attains the highest AEI, indicating the best return per unit of fluctuation. Notably, all QR-based portfolios significantly outperform the classical SW method, generating substantially higher profits.

Method	SW	GE-NL	DS-NL	GE-LTT
Training-H	0.012804	0.013625	0.015416	0.017216
Training-Q	0.012445	0.010977	0.015323	0.016769
Training-M	0.010269	0.010816	0.010017	0.016504
Training-Y	0.011876	0.013343	0.014467	0.011188
Average	0.012046	0.012190	0.013805	0.015419
Improvement	-	1.20%	14.60%	28.00%

Table II. AEI comparison of adaptive mechanism and SW across training lengths

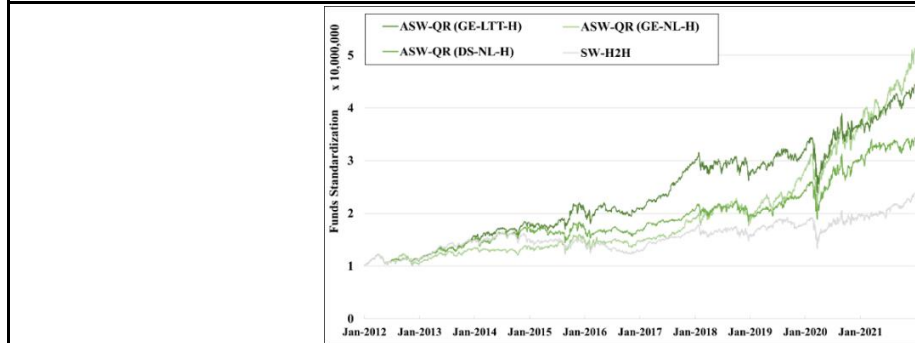


Figure 5. The portfolio trend comparisons are among ASW-QR and the classical SW methods. All the ASW final trends are significantly above SW.

Conclusion

This work presents a quantum-inspired intelligent trading system with QCaaS unifies stock selection and timing decisions. GNQTS efficiently constructs a stable uptrend portfolio by maximizing the trend ratio during training, while the ASW mechanism dynamically adjusts rebalancing timing for timely retraining in non-stationary environments. Three ASW configurations are proposed, each reflecting different market assumptions, and the QR-based approach extends the training trend into testing for robust evaluation. Experimental results confirm the effectiveness of GNQTS in training, ASW monitoring in validation, and dynamic rebalancing in testing, with QR-based ASW consistently outperforming the fixed-length SW method. Overall, this study advances QIO-based intelligent decision-making in complex financial environments. To focus on the effectiveness of the proposed ASW, real-world factors such as transaction costs, slippage, and trading latency were beyond this study's scope and can be examined in future work.

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