

Portfolio Optimisation and Non-Stationary Market Forecasting: Dual Computational Frameworks using Classical and Quantum Algorithms

Extended Abstract for QTML Stellenbosch

Shawal Kassim

Supervisors: Prof. Montaz Ali, Dr. Isaac Nape, Dr. Warren Carlson

School of Computer Science and Applied Mathematics

University of the Witwatersrand, Johannesburg

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Abstract

Modern Portfolio Optimisation is increasingly bottlenecked by the computational demands of high-dimensional, non-stationary financial data. As the number of assets grows, combinatorial solutions expand exponentially, challenging classical high-performance computing capabilities. Quantum Computing, transitioning into the Utility era, presents theoretical algorithmic speedups for such NP-Hard problems. This extended abstract proposes a dual computational framework that solves the Global Mean Variance problem on local JSE SWIX market data. We propose a methodology to denoise Covariance Matrices via a Weighted Nuclear Norm Minimisation algorithm, acting as a preprocessing step. These matrices inform both Classical and Quantum Convolutional Neural Networks (U-Net) to forecast non-stationary market correlations. Finally, the forecasted matrices drive classical (Interior Point Method) and quantum (Quantum Approximate Optimisation Algorithm) solvers for optimal asset allocation. Execution on IBM Utility Quantum Computers investigates practical quantum utility in real-world finance.

Keywords: Quantum Machine Learning, Portfolio Optimisation, QAOA, U-Net, WNNM, JSE SWIX.

1 Introduction

Financial computational strategies rely intrinsically on the ability to acquire high-dimensional optimal solutions swiftly. In modern Quantitative Finance, forecasting the non-stationary dynamics of asset correlations is critical for robust Portfolio Optimisation (PO). Classical approaches are easily out-performed by algorithms leveraging High-Performance Computing (HPC). However, as transistor density reaches physical limitations, QCs offer a fundamentally distinct computational paradigm, manipulating states via superposition and entanglement. With IBM's recent hardware transition from the Noisy Intermediate-Scale Quantum (NISQ) era to the Quantum Utility era, QCs now demonstrate the capacity to solve problems at scales challenging for brute-force classical simulation.

This research, proposed for QTML Stellenbosch, investigates the practical utility of these quantum enhancements. We introduce an end-to-end framework synthesising two historically siloed tracks: Quantum Machine Learning (for forecasting) and Quantum Optimisation (for discrete asset allocation). This framework explicitly targets non-stationary emerging market data, specifically the JSE SWIX, mitigating the Euro-centric bias prevalent in current quantum

finance literature. For comprehensive foundational theories, exhaustive algorithmic configurations, and preliminary empirical analysis, the reader is directed to the complete proposal document, `main.pdf`.

2 Methodological Framework: Denoising and Forecasting

2.1 Weighted Nuclear Norm Minimisation (WNNM)

Empirical Covariance Matrices derived from financial time-series inherently contain statistical noise, leading to the "Markowitz Curse" when inverted for optimisation. To isolate pure market signals, we apply Low-Rank Approximation. Standard Nuclear Norm Minimisation (NNM) applies a uniform penalty to all singular values, inadvertently shrinking dominant market signals. To resolve this, we employ the Weighted Nuclear Norm Minimisation (WNNM) algorithm. By performing Singular Value Decomposition on the noisy matrix $\hat{\Sigma}_{\text{noisy}}$, WNNM calculates an adaptive weight $w_i = \frac{\lambda}{\sigma_i + \epsilon}$ for each singular value σ_i . This ensures that larger eigenvalues (market signals) are preserved, while smaller eigenvalues (idiosyncratic noise) are aggressively penalised, yielding a robust, positive semi-definite $\hat{\Sigma}_{\text{denoised}}$.

2.2 Classical and Quantum Convolutional Neural Networks

The denoised matrices, $\hat{\Sigma}_{\text{denoised}}$, construct the supervised dataset for forecasting future market structures, mapping $\Sigma_t \rightarrow \Sigma_{t+1}$. The classical baseline uses a parameterized U-Net Classical Convolutional Neural Network (CCNN) with skip connections to process spatial asset relationships. To investigate potential quantum supremacy, we construct a Quantum Convolutional Neural Network (QCNN). The classical continuous data is embedded into a quantum Hilbert space using an AngleEncoding feature map over N_{qubits} . The QCNN employs parameterized two-qubit unitary operators $U_{\text{conv}}(|\phi\rangle)$ interspersed with quantum pooling. To perform generative reconstruction (upsampling) without violating the no-cloning theorem, the QCNN deploys a novel quantum analogue for skip connections: Two-Local unitary gates uniformly distribute quantum information from the bottleneck back to idle qubits omitted during encoding, achieving high-fidelity latent representation prior to measurement.

3 Combinatorial Quantum Optimisation

3.1 The Global Minimum Variance Problem

Following the forecasting phase, we solve the Global Minimum Variance (GMV) PO problem, which focuses purely on risk minimization, avoiding error-prone expected return predictions. The continuous objective minimizes the portfolio variance $\mathbf{x}^\top \hat{\Sigma}_{\text{pred}} \mathbf{x}$ subject to a fully invested budget constraint ($\sum x_i = 1$) and long-only boundaries ($\mathbf{x} \geq 0$). While the classical pipeline solves this strictly convex Quadratic Program using an Interior Point Method (IPM), the quantum pipeline requires transforming the continuous space into a discrete Combinatorial Optimisation Problem.

3.2 QUBO and QAOA Implementation

Continuous weights x_i are discretized using a K -bit binary expansion: $x_i \approx \sum_{k=1}^K 2^{-k} z_{i,k}$. The constraints are shifted into the objective via a penalty scalar λ , constructing a Quadratic Unconstrained Binary Optimisation (QUBO) model. Using the linear substitution $z_{i,k} \rightarrow \frac{1 - \sigma_\mu^z}{2}$, we map the QUBO to an Ising Hamiltonian representing the problem cost, $H_C = \sum_\mu h_\mu \sigma_\mu^z + \sum_{\mu < \nu} J_{\mu\nu} \sigma_\mu^z \sigma_\nu^z$.

We deploy the Quantum Approximate Optimisation Algorithm (QAOA) on IBM Utility processors (e.g., `ibm_strasbourg`, 156 qubits). QAOA initializes a superposition state and iteratively applies alternating unitary operators: the phase operator $U(\gamma) = e^{-i\gamma H_C}$ and the transverse-field mixer operator $U(\beta) = e^{-i\beta H_B}$, where $H_B = \sum_{\mu} \sigma_{\mu}^x$. Classical optimisers (e.g., COBYLA, SPSA) iteratively update variational parameters γ, β to minimize the expectation value $\langle \psi(\gamma, \beta) | H_C | \psi(\gamma, \beta) \rangle$. Given the inherent noise of real quantum hardware, we leverage IBM’s error mitigation primitives and dynamic circuits to suppress readout and two-qubit gate errors.

4 Expected Contributions and Conclusion

This research establishes a highly interdisciplinary pipeline merging Quantum Machine Learning with Quantum Optimisation. By evaluating execution times and solution distributions derived from the IBM Utility hardware against exact MIP/IPM classical solvers, we aim to empirically quantify the extent of quantum advantage in high-dimensional non-stationary financial forecasting. Initial hypotheses, detailed in `main.pdf`, suggest that while classical solvers currently dominate execution speed, the quantum formulation provides a scalable architectural advantage for exponentially vast combinatorial search spaces.

References

- [1] Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77-91.
- [2] Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies*, 33(5), 2223-2273.
- [3] Cong, I., Choi, S., & Lukin, M. D. (2019). Quantum convolutional neural networks. *Nature Physics*, 15(12), 1273-1278.
- [4] Farhi, E., Goldstone, J., & Gutmann, S. (2014). A quantum approximate optimization algorithm. *arXiv preprint arXiv:1411.4028*.
- [5] Kassim, S. (2026). *Portfolio Optimisation and Non-Stationary Market Forecasting: Dual Computational Frameworks using Classical and Quantum Algorithms*. `main.pdf` (Research Proposal).