

# Quantum-Enhanced Portfolio Optimization

A Hybrid Factor-QAOA Approach

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# Project Summary

- Our project focuses on creating a robust hybrid quantum-classical framework:
  1. how to efficiently solve high-dimensional optimization problem to help in ETF creations and index tracking.
  2. how to address challenges in portfolio optimization, especially the noisy and unstable estimation of asset return covariance matrices.

Within the project, the quantum-enhanced optimized portfolio's performance is compared against a classical minimum variance portfolio benchmark : GUROBI on the metrics of annualized returns, Sharpe Ratio, and risk (standard deviation).

The project demonstrates the feasibility of applying hybrid quantum algorithms to complex financial challenges and their potential to uncover more efficient and diversified portfolios that perform well in the real-world scenarios.



# Key Features

## 1. Robust Factor Model via PCA

- Identifies latent, uncorrelated risk factors for stable covariance matrices, reducing the impact of noise and estimation errors.

## 2. Classical Portfolio Optimization Benchmark

- Provides a quantifiable baseline for comparison to evaluate quantum advantage.

## 3. Precise QUBO Problem Formulation

- Maps financial problems under the balancing risk minimization, return maximization, and strict adherence to a cardinality constraint to a QUBO matrix.

## • 4. PennyLane for QAOA Core

- Utilizes PennyLane for constructing, executing, and optimizing the QAOA circuit, abstracting low-level quantum gate operations.

## 5. Systematic Hyperparameter Tuning

- Implements a robust grid search to explore multi-dimensional hyperparameter space, including risk aversion, penalty strength, and QAOA layers.

# Factor Model for Covariance Estimation

- We implement a statistical factor model using Principal Component Analysis (PCA). The underlying assumption is that a substantial portion of asset return variance can be explained by a few common factors, with the remaining variance attributed to idiosyncratic (asset-specific) risk.
- The robust covariance matrix is reconstructed using the factor model equation:  $\Sigma = B\Sigma_f B^T + D$

where  $\Sigma_f$  = Factor Covariance matrix

$B$  = Factor Loadings vector

$D$  = Diagonal Idiosyncratic Covariance

# Portfolio Optimization as a QUBO Problem

- Our problem aims to minimize risk, maximize return, and enforce cardinality constraints, combined into a single cost function.

$$C(\mathbf{x}) = \mathbf{x}^T \Sigma \mathbf{x} - q \cdot \boldsymbol{\mu}^T \mathbf{x} + \lambda \left( \sum_{i=1}^N x_i - K \right)^2$$

- To leverage quantum computing, portfolio selection is mapped into a Quadratic Unconstrained Binary Optimization (QUBO) format.

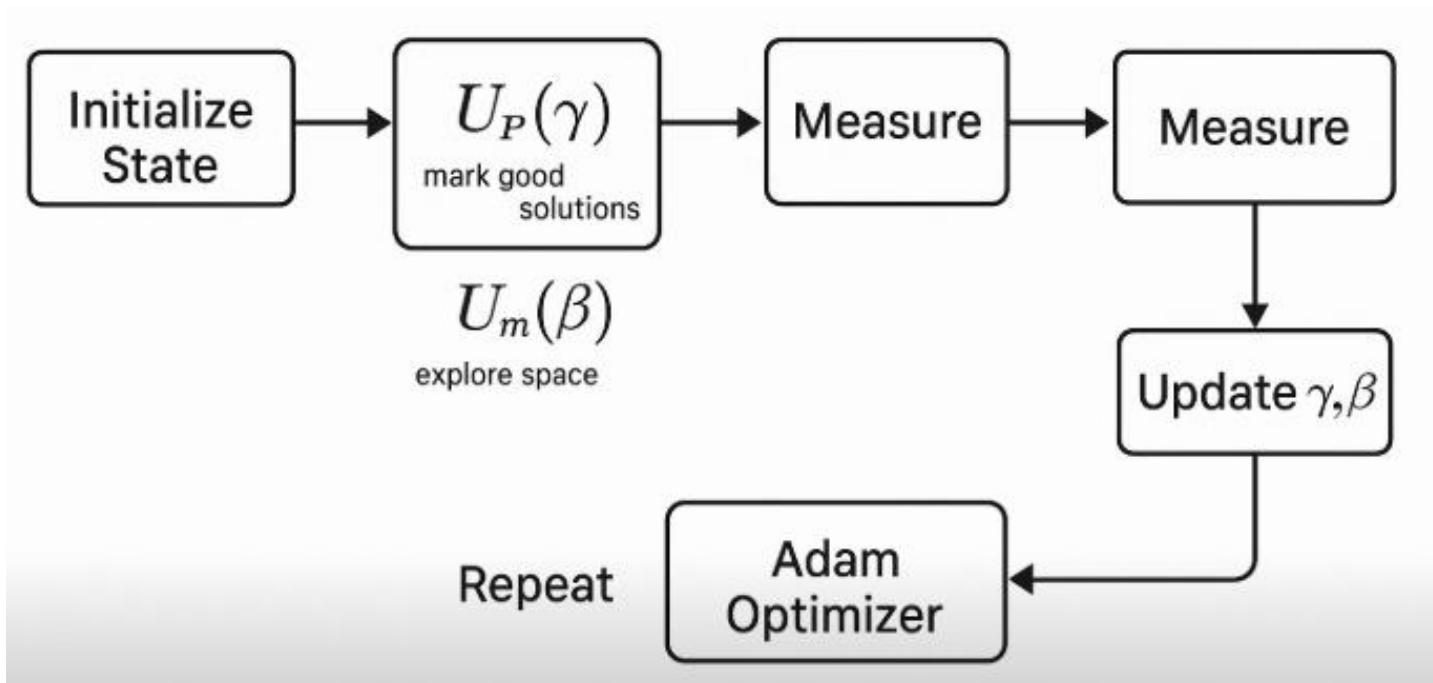
Minimize  $C(\mathbf{x}) = \mathbf{x}^T \mathbf{Q} \mathbf{x}$  where  $\mathbf{x}$  is a vector of binary decision variables ( $x_i \in \{0,1\}$ , 1 if asset  $i$  is selected).  
QUBO matrix  $\mathbf{Q}$  is constructed as:

- $Q_{ii} = \Sigma_{ii} - q \cdot \mu_i + \lambda(1 - 2K)$
- $Q_{ij} = \Sigma_{ij} + 2\lambda$  (for  $i \neq j$ , contributing to  $Q_{ij}x_i x_j + Q_{ji}x_j x_i$ , where  $\mathbf{Q}$  is symmetric)

# QAOA Implementation with PennyLane

- QAOA is a powerful variational quantum algorithm, operating by adjusting parameters of a quantum circuit, which then generates a quantum state from which solutions can be sampled.
- **Quantum Device Initialization**
- We use `lightning.qubit` simulator.
- Using "wires = num\_qubits": Each qubit represents an asset ( $x_i$ ), so  $\text{num\_qubits} = \text{num\_assets}$
- Using shots = 10000 : crucial parameter for `qml.sample` measurements which is essential to obtain statistically meaningful distributions.
- We thereby construct the Cost Hamiltonian and the Mixer Hamiltonian which are required for the QAOA solver.

# QAOA workflow



- Initialization of the quantum state.
- Alternating Problem Unitary  $U_P(\gamma)$  to encode portfolio cost and Mixer Unitary  $U_M(\beta)$  to explore solutions.
- Measurement of the cost (objective function).
- Classical optimization (Adam) to update parameters  $\gamma, \beta$
- Repetition of the loop until convergence to the optimal portfolio.

# Hyperparameter Tuning

- QAOA's performance hinges on its hyperparameters, which are external to the quantum circuit's variational parameters and are tuned classically through an exhaustive grid search.
- The tuning process iterates through every hyperparameter combination, involving these crucial steps:

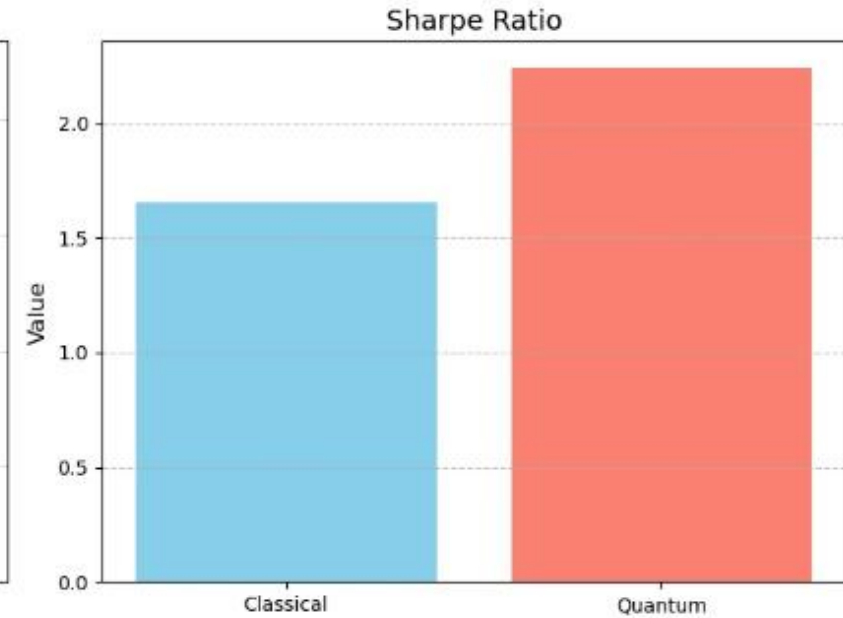
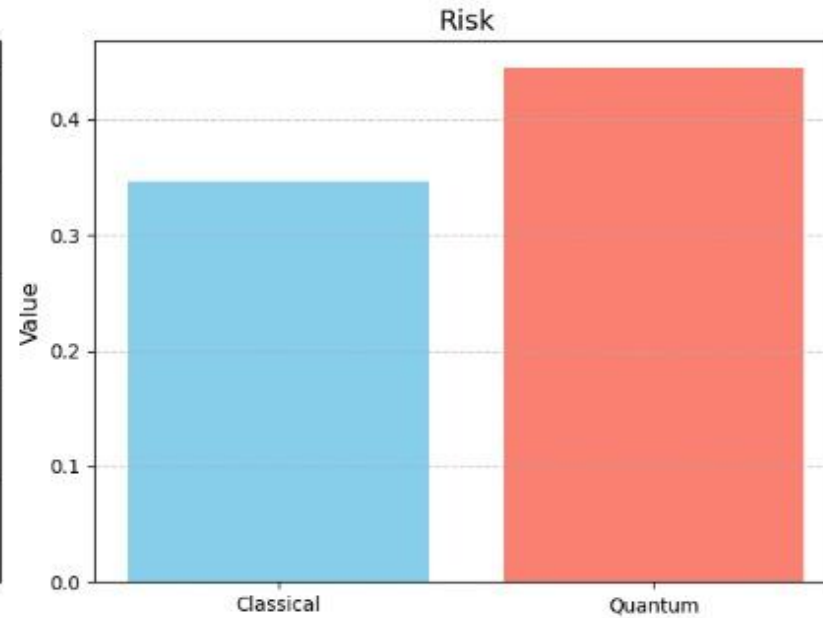
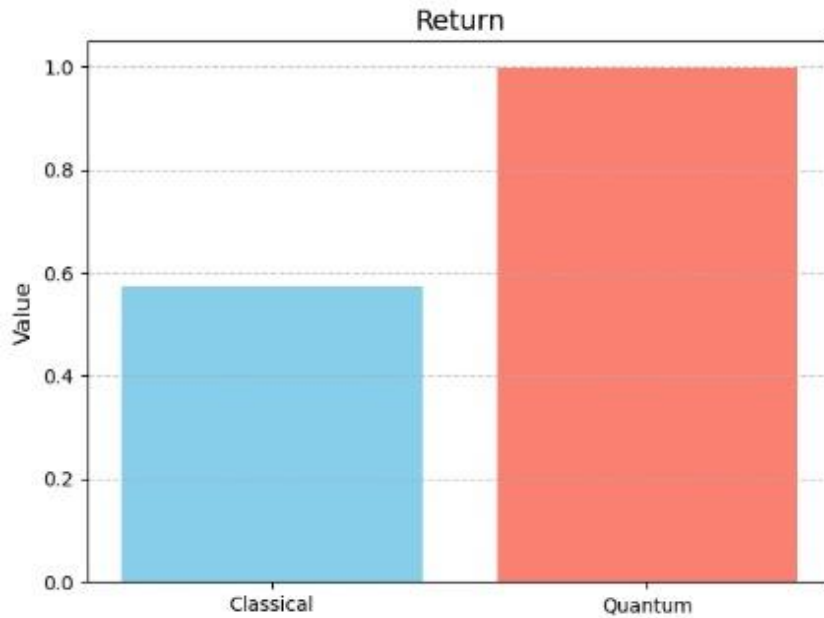
- 1 QUBO Construction : rebuilding the QUBO problem for each combination
- 2 Multiple QAOA Runs : common practice to mitigate the problem of local minima in variational algorithms.
- 3 Best Parameter Selection : Identify optimal  $\gamma$  &  $\beta$  angles
- 4 Solution Evaluation : evaluation of valid bitstrings that satisfy constraints
- 5 Best Portfolio : the bitstring for specific hyperparameter combination with highest Sharpe Ratio is identified





# QAOA portfolio optimization results

Classical vs Quantum Portfolio Performance

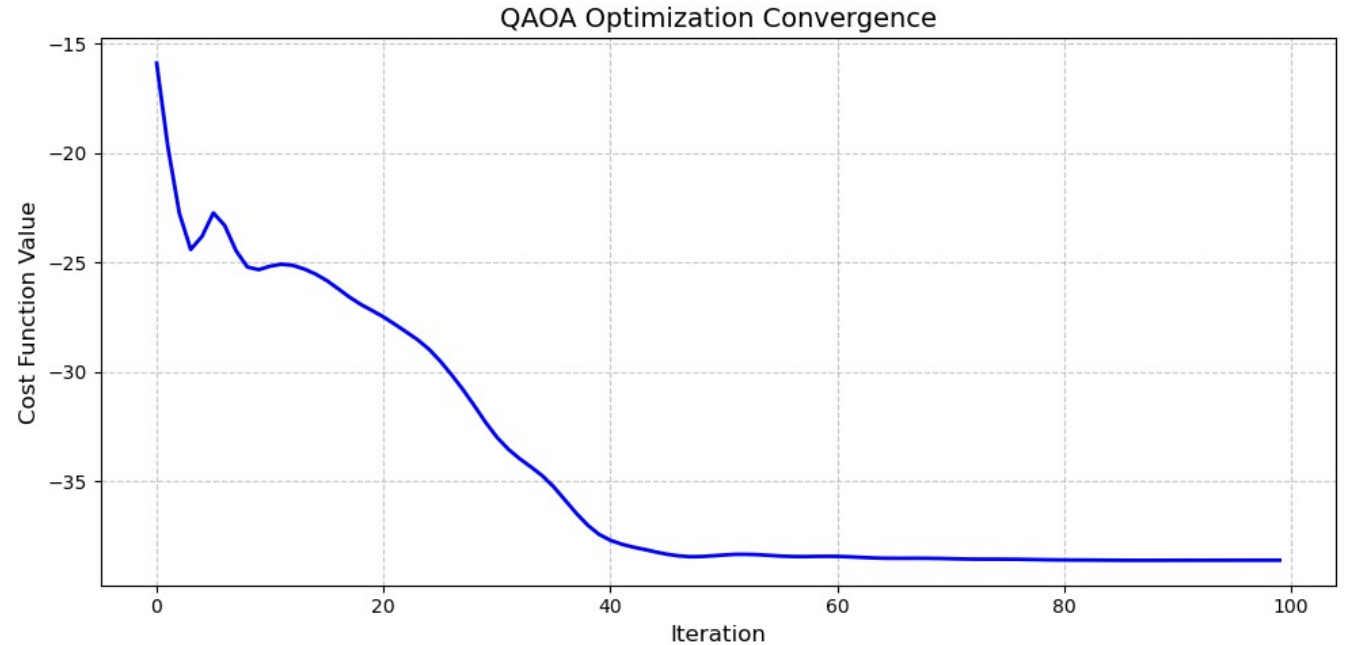


# QAOA portfolio optimization results

Cost function steadily minimized, and stabilizes around iteration 50, showing the successful parameter optimization.

## Overall Best QAOA Portfolio

- Found via exhaustive hyperparameter search.
- Achieved highest Sharpe Ratio across all configurations.



# Future Enhancements

- This project lays a robust foundation for quantum-enhanced portfolio optimization, with several exciting avenues for future work.

## 1. **Advanced Hyperparameter Optimization**

- Adaptive and Dynamic Tuning
- Beyond Grid-search : RL, Bayesian Optimization, Random Search, etc.

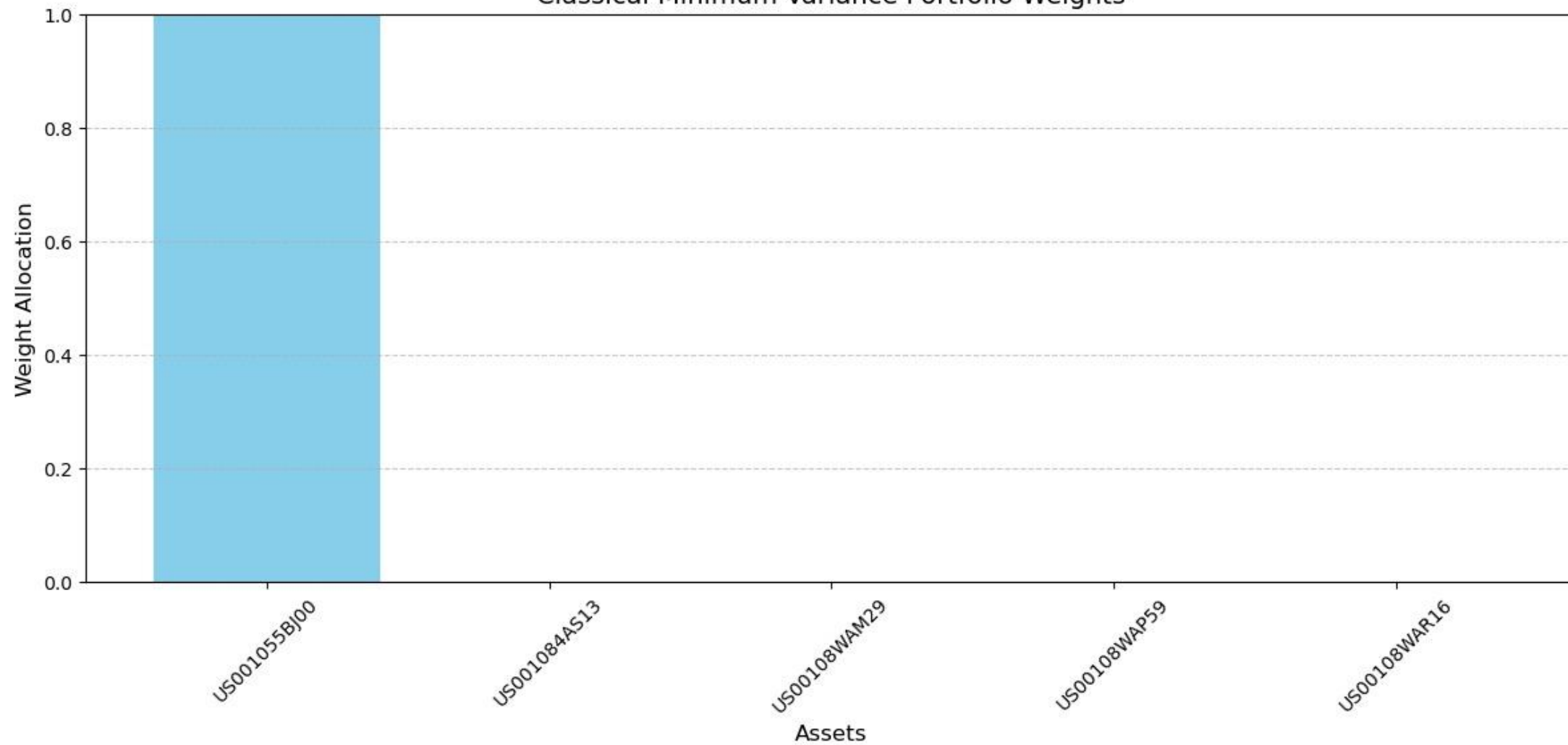
## 2. **Exploring Sophisticated QAOA Ansätze**

- Experiment with custom mixer Hamiltonians that may lead to faster convergence.
- Higher Layer Depths

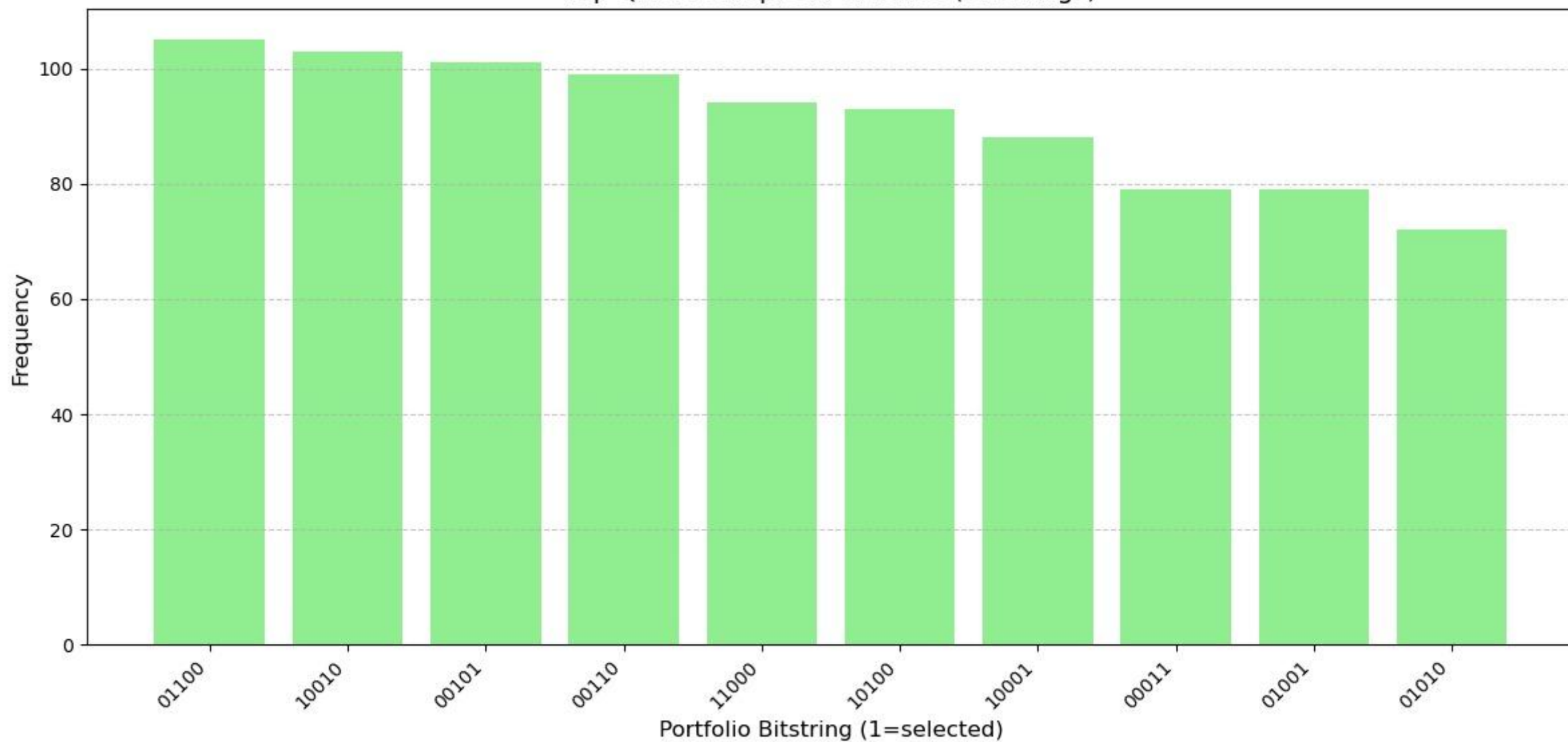
## 3. **Integration with other Quantum Algorithms**

- Integration with VQE, Quantum Annealing, or Grover's Algorithm

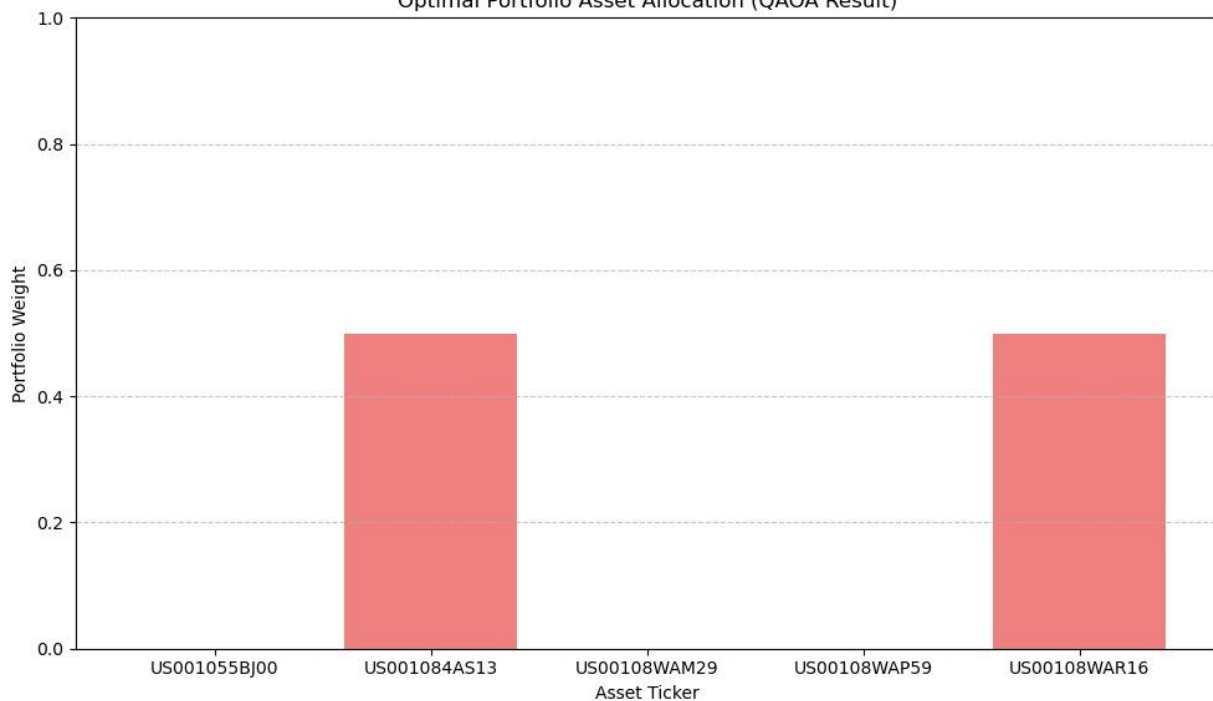
Classical Minimum Variance Portfolio Weights



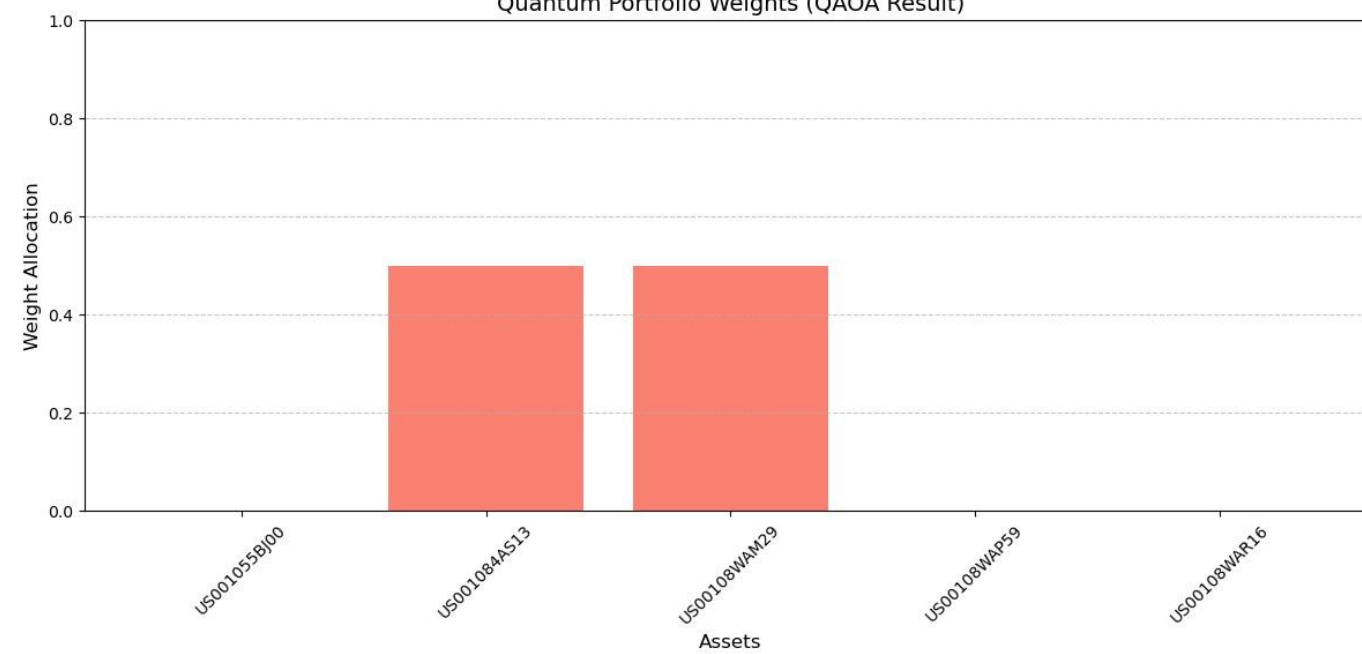
Top QAOA Sampled Portfolios (Bitstrings)



Optimal Portfolio Asset Allocation (QAOA Result)

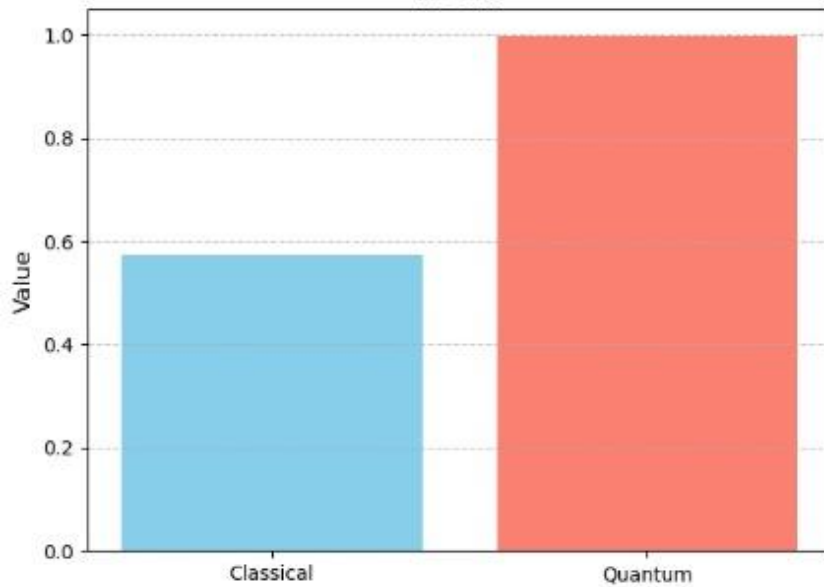


Quantum Portfolio Weights (QAOA Result)

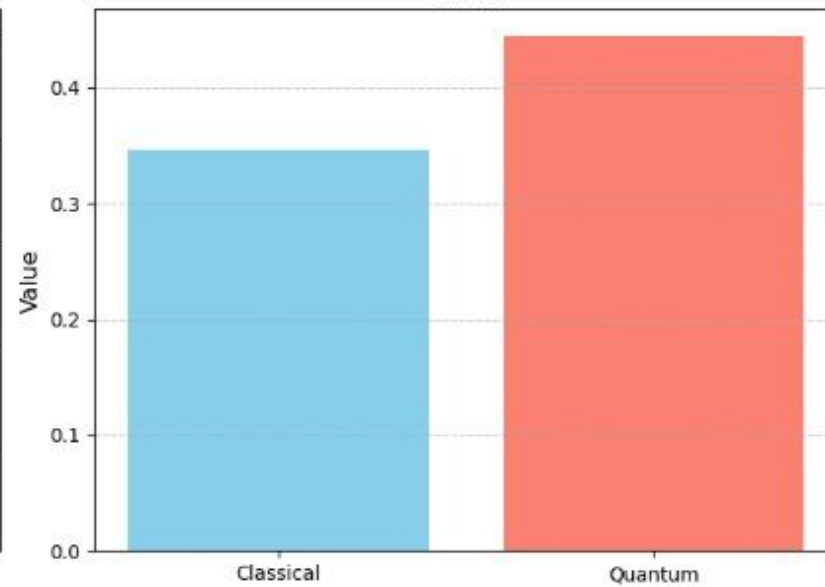


## Classical vs Quantum Portfolio Performance

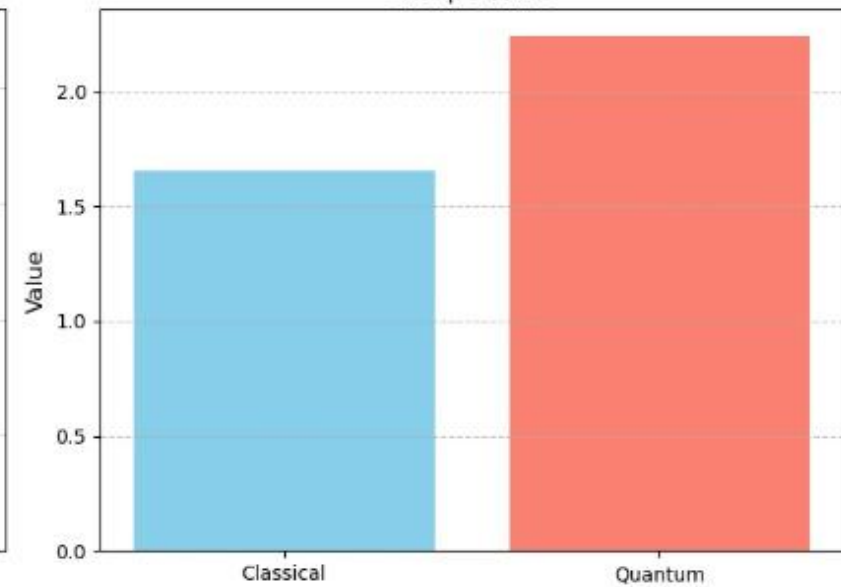
Return



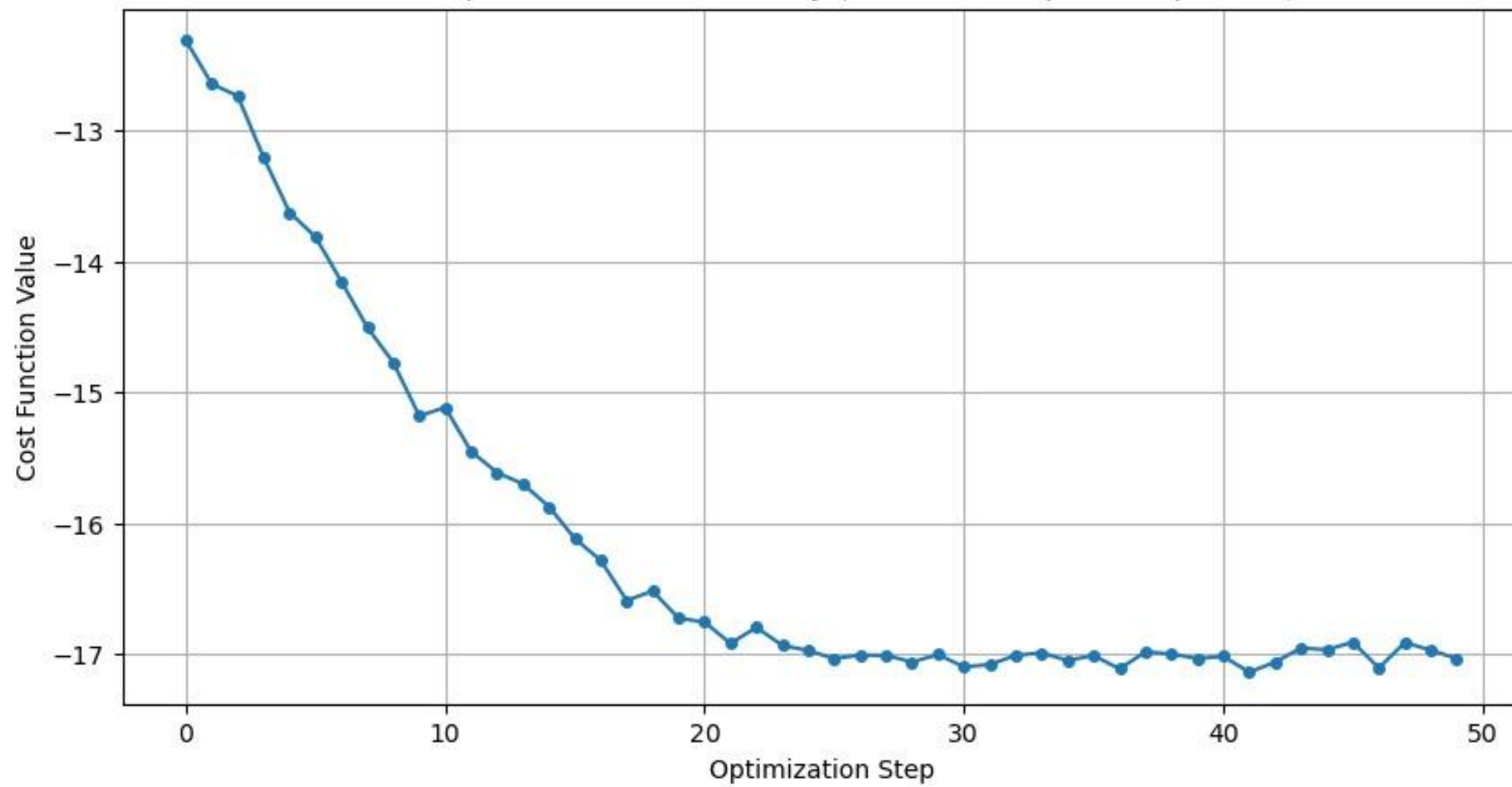
Risk



Sharpe Ratio



QAOA Optimization Cost History (Best HP Set:  $p=1$ , step=0.01)





--- Overall Best QAOA Portfolio from Tuning ---

Optimal Hyperparameters: q\_risk\_aversion=0.1, lambda\_penalty=5.0, p\_layers=1, stepsize=0.01

Best QAOA Portfolio (by Sharpe Ratio) Bitstring: 01001

Selected Assets: ['US001084AS13', 'US00108WAR16']

Number of selected assets: 2

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QUBO Matrix (Q) for Overall Best QAOA Portfolio:

|              | US001055BJ00 | US001084AS13 | US00108WAM29 | US00108WAP59 | \ |
|--------------|--------------|--------------|--------------|--------------|---|
| US001055BJ00 | -14.937015   | 10.177864    | 10.129394    | 10.151953    |   |
| US001084AS13 | 10.177864    | -14.862626   | 10.192775    | 10.226383    |   |
| US00108WAM29 | 10.129394    | 10.192775    | -14.929957   | 10.164691    |   |
| US00108WAP59 | 10.151953    | 10.226383    | 10.164691    | -14.891143   |   |
| US00108WAR16 | 10.165380    | 10.246386    | 10.179243    | 10.210493    |   |

|              | US00108WAR16 |
|--------------|--------------|
| US001055BJ00 | 10.165380    |
| US001084AS13 | 10.246386    |
| US00108WAM29 | 10.179243    |
| US00108WAP59 | 10.210493    |
| US00108WAR16 | -14.880095   |

Cost Hamiltonian (H\_cost) for Overall Best QAOA Portfolio:

$$\begin{aligned} & -11.789276712471644 * I([0, 1, 2, 3, 4]) + -2.687640556951498 * Z(0) + -2.7795395029301155 * Z(1) + 2.544466122107877 * (Z(0) @ Z(1)) \\ & + -2.7015475358554144 * Z(2) + 2.5323485950674423 * (Z(0) @ Z(2)) + -2.7428087843127735 * Z(3) + 2.53798828514735 * (Z(0) @ Z(3)) \\ & + -2.7603278570831256 * Z(4) + 2.541344900137121 * (Z(0) @ Z(4)) + 2.5481937069481377 * (Z(1) @ Z(2)) + 2.556595851474747 * (Z(1) @ Z(3)) \\ & + 2.5615966163864057 * (Z(1) @ Z(4)) + 2.5411728343976585 * (Z(2) @ Z(3)) + 2.5448108336538624 * (Z(2) @ Z(4)) \\ & + 2.5526232042839694 * (Z(3) @ Z(4)) \end{aligned}$$

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