

Quantum Finance

Q-Frontier

Task 1

For this task, we built a simplified bond portfolio optimization test using randomly generated prices, trade factors, characteristics, and bucket assignments. The objective is the squared deviation from target bucket-characteristic totals, with constraints on portfolio size, cash, and floors. The `evaluate()` function scores candidate portfolios and checks constraint violations. Five random portfolios were tested and visualized with a seaborn heatmap.

Task 2

The original portfolio optimization uses binary variables (1=selected, 0=not) with constraints including sector PMV targets, sector PMV/DXS limits, cash bounds, and bond-specific trading rules. As quantum algorithms (QAOA/VQE) require unconstrained Quadratic Unconstrained Binary Optimization (QUBO) or Ising forms, this constrained combinatorial problem must be transformed. Using the penalty method, each constraint is converted to a quadratic penalty term: (Sum of each bond's contribution metric minus the target value) squared, multiplied by a penalty weight. The coefficient is the bond's metric contribution, the target is the constraint's goal, and the weight controls violation severity. The final QUBO objective combines the original goal and all constraint penalties. Binary variables are mapped to spin variables (± 1), with 0 and 1 as opposite spin states. Substituting this into the QUBO yields an Ising Hamiltonian—a sum of single spins, spin pairs, and a constant—implementable via Pauli-Z operators on qubits for quantum optimization.

Task 3

Once the unconstrained Hamiltonian is built, the next step is to solve it using a quantum optimization routine. For this task, we employed the Quantum Approximate Optimization Algorithm (QAOA) to solve the unconstrained Hamiltonian. QAOA is a variational algorithm using a parameterized quantum circuit built from alternating layers:

- Cost Unitary: Applies the problem Hamiltonian to evolve the state towards better solutions.
- Mixer Unitary: Applies rotations to explore different configurations. Classical optimization tunes the circuit's parameters (for cost and mixing steps) to minimize the expected energy of the prepared state, which measures solution quality.

The outcomes are analyzed via:

- Lowest Energy Found: Indicates solution optimality.
- Convergence Profile: An energy-versus-iteration graph showing optimization progress.
- Top Candidate Portfolios: The most probable solutions, checked for compliance with sector, cash, and risk constraints.

This unified process translates the business problem into a quantum-ready Hamiltonian via penalties and solves it using QAOA's hybrid quantum-classical approach.

Task 4

A classical optimization routine was used as a benchmark to validate the QAOA and VQE results by evaluating their selected bond portfolios under the same hard constraints, checking feasibility, and comparing objective values to the classical optimum to measure performance gaps.

Task 5

The QAOA and VQE masks, representing selected bond portfolios, were evaluated against the benchmark LP model to check feasibility and performance. Initial selections showed potential sector PMV/DXS constraint violations, so a greedy repair process was applied to meet all limits and adjust the bond count to target. After repair, both masks became fully feasible and their objective values were computed and compared to the benchmark optimum, with results saved in both x_* and $iTrade_*$ formats for consistent tracking and analysis.