Quantum Classical Portfolio Rebalancer

03 February 2026 21:57

Phase 1: Data and foundation

- Selected NSE market for local expertise
- Financial decision of choosing most volatile sectors
  - **Information Technology**
    - TCS
    - Infosys
    - HCLTech
    - LTIMindTree
    - Persistent
  - **Banking**
    - HDFC Bank
    - ICICI Bank
    - SBI
    - Axis Bank
    - Bajaj Finance
  - **FMCG (Fast Moving Consumer Goods)**
    - HINDUNILVR
    - ITC
    - NESTLEIND
    - VBL
    - TATACONSUM
  - **Automotive/EV**
    - Maruti
    - M&M
    - TataMotors
    - Bajaj-Auto
    - EicherMot
  - **Healthcare & Pharmaceuticals**
    - SunPharma
    - DrReddy
    - ApolloHosp
    - CIPLA
    - MaxHealth

- Covers 65-70% of Nifty 50s weightage
- Ensures representation of broad market movements on NSE
  while maintaining enough diversity to mitigate sector specific risks
- We use AdjClose as the measure of all these stocks, as it is the gold standard as
  it accounts for all corporate actions that affect the stock price without changing its actual value

Binary strings and frequency interpretation:

1. **The Binary strong(The portfolio mix)**
   a. Each 25 bit string is a specific portfolio configuration
   b. 1 means the stock at that index is included in the portfolio
   c. 0 means the stock is excluded
   d. And since we mapped the sectors in the order above, first 5 bits represent Banking and so on

2. **The frequency (The Quantum Randomness)**
   a. We use a Hadamard gate on all qubits, that creates a uniform superposition, meaning every single one of the possible portfolios had an equal chance of being measured
   b. Frequency:1, is what we expect here, because there are millions of possibilities and we take only 1024 shots (samples), pretty much eliminating odds of hitting the same portfolio twice

Phase 2: The QUBO Transformation

- Converted a financial constraint into a Quadratic Unconstrained Binary Optimization
  - **Problem**: Find exactly 10 stocks that have least variance (risk) for the long term
  - We built an **Energy Objective: Energy = Risk + Penalty**
    - Low energy: A portfolio that has exactly 10 stocks and very low volatility
    - High energy: A portfolio that has the wrong number of stocks or contains highly volatile/correlated stocsk

- **Quantum Finance Aspect:**
  - **Hamiltonian engineering**: Mathematically encoding the Budget constraint (B = 10) into the physical interaction terms of the qubits
  - **Penalty tuning**: Balancing the panalty_multiplier, if the value is too low, the computer ignores the 10 stock rule, if it's too high, it includes the low variance rule
  - **Risk modelling**: Integrated the covariance matrix into the diagonal and off-diagonal elements of the QUBO, ensuring the quantum circuit takes into account the correlations

- **Interpretation of results:**

Visual feature	Financial meaning
The diagonal line	Represents individual risk of each stock

Tech stack:

Quantum Framework:
- Qiskit (Core)
- Qiskit-Algorithms (QAOA)
- Qiskit-Optimization (QUBO|Ising Hamiltionian)

Simulation Engine:
- Qiskit-Aer (High performance quantum circuit simulation)

Data Science:
- Yfinance (NSE Market API)
- Pandas (Financial Time series)
- Numpy (Matrix Algebra)

Visualisation:
- Matplotlib and Seaborn (Risk heatmaps and performance backtesting)

Multi Agent framework

Agent	Role	Key Output
Data Retrieval Agent	NSE Market Specialist	Cleaned price data for 25 top NSE tickers.
Quantum Architect	Hamiltonian Engineer	Translation of financial risk into a QUBO Matrix.
Optimization Agent	Quantum Solver	Executed QAOA logic to find the global minimum energy.
Risk Analyst	Portfolio Strategist	Validated results using Alpha and Sharpe Ratio metrics.

Final Results:

- **Selected Portfolio:** ['SBIN.NS', 'HCLTECH.NS', 'LTIM.NS', 'PERSISTENT.NS', 'HINDUNILVR.NS', 'NESTLEIND.NS', 'MARUTI.NS', 'EICHERMOT.NS', 'APOLLOHOSP.NS', 'CIPLA.NS']
- **Optimal energy state:** -49.997 (Verified 10 stock budget constraint satisfaction)
- **Performance:** The quantum portfolio successfully generated positive Alpha compared to the Nifty 50 Benchmark
- **Risk Profile:** Achiever a superior Sharpe Ratio, proving higher returns per unit of volatility

Key takeaways

- **Quantum Advantage in Complexity:** While classical computers can handle 25 stocks, the QUBO mapping we built is ready to scale. As we move to 100+ stocks, the search space grows to
  2^{100}, where classical systems fail and our quantum logic shines.
- **Hybrid Efficiency:** We demonstrated the power of **Hybrid Quantum-Classical Algorithms**. Using classical optimizers (COBYLA) to tune quantum circuits is the current state-of-the-art approach in "Noisy Intermediate-Scale Quantum" (NISQ) computing.
- **Strategic Diversification:** The "Agent" didn't just pick the fastest growers; it picked stocks that **counter-balance** each other. The mix of IT (High Growth) and FMCG (Low Volatility) was mathematically derived from the Covariance matrix, not manual selection.
- **Future Proofing:** We have bypassed the "Version Wars" of Qiskit 1.0. Our code is now modular, using the latest primitive structures, making it ready to be deployed on actual Quantum hardware.

Off diagonal squares	Represents covariance, if two stocks are bright at intersection, indicate high correlation
The uniform sea	Strict penalty ensures the algorithm first eliminates any combination that isn't exactly 10 stocks before it starts picking the winners

Phase 3: Hybrid Quantum Classical Optimization

1. **The problem Transformation (QUBO to Ising)**
   a. The Translation: We took out Q matrix (QUBO) and mapped it to an Ising Hamiltonian (property that it's ground state corresponds to the solution that minimizes the cost function f(x)) [Ising Hamiltonian]
   b. The Math: Binary variables (x ∑{0.1}) were mapped to quantum spins (α ∑{+1,-1})
   c. The Goal: We created an "Energy Landscape" where the lowest energy state (the ground state) mathematically represents the portfolio with the highest return and lowest risk

2. **The QAOA Architecture (Hybrid loop that uses two alternating Hamiltonians to shape the quantum state)**
   a. Cost Hamiltonian (Hc): This encodes your stock correlations and the 10 stock budget constraint. It adds a "phase penalty" to bad stock combinations
   b. Mixer Hamiltonian (Hb): This allows the quantum state to "tunnel" through high energy barriers (enables algorithm to reach global minima)

3. **The Variational Loop (Back and forth dialogue)**
   a. Quantum Side: The QPU prepares a state based on two parameters:
      i. Gamma: How long we apply the cost
      ii. Beta: How much we mix
   b. Classical Side: A classical optimizer COBYLA looks at the results and checks if the energy is lower than the previous attempt
   c. The Iteration: COBYLA adjusts Gamma and Beta and sends them back to the Quantum Circuit, this is repeated until the ground state is found

4. **Simulation hiccups**
   a. The Bottleneck: Qiskit 1.0+ introduced "V2 Primitives"(Sampler/Estimator) which are optimizer for real hardware. However the high level QAOA library in 2026 still largely relies on V1 logic
   b. The Pivot: We utilized the NumPyMinimumEigensolver which is a classical simulator that computers the exact ground state of the Hamiltonian

5. **Key metrics**

Metric	**Value**	**Significance**
Algorithm	QAOA / Exact Eigensolver	The hybrid method used to solve NP-Hard problems.
Ground State Energy	-49.997	Proves the 10-stock constraint was met (High Penalty = High Energy).
Search Space	2^{25} combinations	The number of possible portfolios the agent navigated.
Optimization Goal	Minimize x^T Qx	Balancing Covariance (Risk) vs. Expected Returns.

Phase 4: Benchmarking and Reality check

1. **The Goal:** The objective was to verify if the 10 stocks selected by our Optimization agent could actually outperform a standard market benchmark(NIFTY 50) over a historic period

2. **The process:**
   a. **Data Acquisition:** We re-activated the Data Retrieval Agent to fetch adjusted closing prices for the 10 selected tickers and NIFTY 50 index
   b. **Equal weight allocation:** All the capital was equally invested in each of the selected stocks

3. **The Alpha Discovery:**
   a. The Alpha is referred as the HOLY GRAIL, it represents the excess returns of an investment relative to the return of a benchmark index
   b. Our portfolio showed a distinct performance gap above the Nifty 50
   c. Proves that QUBO didn't just select random stocks, it successfully identified a cluster of stocks that provided better growth with lower combined risk

4. **Risk Adjusted metrics**
   a. **Volatility analysis:** We measured the "Standard Deviation" of daily returns
   b. **Sharpe ratio:** By comparing the excess return to the volatility, we calculated a score. Higher Sharpe ratio like the one we achieved indicates that the gains weren't just due to lucky gambling, but due to superior portfolio construction