Quantum Risk Engineering: Accelerating VaR Analysis with IQAE and Soft-CVaR

iQuHACK 2026 Submission

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1 Problem Description & Probability Model

Value at Risk (VaR) is the standard metric for quantifying financial risk, answering the fundamental question: *"What is the maximum amount I could lose with α% confidence?"*

For this challenge, we modeled an asset return probability distribution over a fixed time horizon using a **Gaussian distribution** with the following parameters:

- Mean return (μ): 15%
- Standard deviation (σ): 20%

Our goal was to estimate the VaR at high confidence levels (95% and 99%) and rigorously compare the computational resources required to achieve a target estimation error (ϵ) using classical versus quantum methods.

2 Classical Benchmark: Monte Carlo Simulation

As a baseline, we implemented a classical Monte Carlo simulation to establish a performance floor. The workflow involved:

1. Sampling N independent returns from the defined Gaussian distribution.
2. Sorting the samples to form an empirical Cumulative Distribution Function (CDF).
3. Extracting the $(1 - \alpha)$-quantile as the VaR estimate.

Results: As expected, the classical error scaled according to the Central Limit Theorem:

$$\epsilon \propto \frac{1}{\sqrt{N}} \tag{1}$$

This scaling confirms that to improve precision by a factor of 10, the classical approach requires 100 times more samples—a prohibitive computational cost for high-frequency, high-precision risk calculations in a live trading environment.

3 Quantum Workflow: IQAE & Bisection Search

Leveraging the **Classiq SDK**, we developed a quantum algorithm to estimate VaR without relying on massive sampling.

3.1 Circuit Architecture

- **State Preparation:** We encoded the Gaussian probability distribution directly into the amplitudes of a quantum state using Classiq's logic synthesis engine.
- **Threshold Oracle:** We constructed a comparator oracle that flips a target qubit if the encoded value is below a specific threshold (representing a tail event).
- **Estimation Routine:** Instead of simple sampling, we employed **Iterative Quantum Amplitude Estimation (IQAE)**. Unlike standard QAE, IQAE does not require Quantum Phase Estimation (QPE), allowing for reduced circuit depth while maintaining the Heisenberg scaling advantage.

3.2 The Search Algorithm

To find the specific VaR threshold, we wrapped the IQAE routine in a classical **Bisection Search**. The algorithm iteratively guesses a threshold K, estimates the cumulative probability $P(X \leq K)$ using IQAE, and adjusts the search window until the probability converges to $1 - \alpha$.

4 Comparison & Sensitivity Analysis

4.1 Accuracy vs. Queries (The Quantum Advantage)

We performed a rigorous head-to-head comparison of convergence rates.

- **Classical:** Exhibited the standard $\mathcal{O}(1/\epsilon^2)$ convergence.
- **Quantum:** Our IQAE implementation demonstrated a convergence scaling of approximately $\mathcal{O}(1/\epsilon)$.

estimation_error_IQAEvsmc.png

Figure 1: Log-log plot showing the estimation error ϵ decreasing significantly faster for the Quantum (IQAE) method compared to Classical Monte Carlo as the number of oracle calls increases.

4.2 Sensitivity Analysis

- **Confidence Levels:** At higher confidence levels (e.g., 99%), classical methods struggled to capture rare tail events without increasing N drastically. The quantum method, leveraging amplitude amplification, identified these tail probabilities more efficiently.
- **Discretization (Qubit Count):** We analyzed the impact of grid resolution on accuracy. Using fewer qubits (e.g., 7) introduced discretization artifacts (step-like CDFs), while higher qubit counts (e.g., 15) smoothed the distribution, reducing modeling error at the cost of circuit depth.

15_qubit_analysis.png

Figure 2: Analysis of distribution smoothness and tail event capture using 15 qubits.

5 Novel Extension: The "Soft-CVaR" Architecture

Beyond the standard comparison, we developed a novel variational approach for **Conditional Value at Risk (CVaR)** to address the "discontinuity bottleneck" in standard quantum algorithms.

By applying **Fenchel-Moreau analytic smoothing**, we replaced the sharp indicator functions typically used in risk analysis with smooth approximations. This allows us to use **Variational Quantum Signal Processing (V-QSP)** to approximate the risk function.

- **Key Innovation:** This method reduces the polynomial approximation degree required from $\mathcal{O}(1/\epsilon)$ to $\mathcal{O}(\log(1/\epsilon))$.
- **Impact:** This theoretically allows for risk estimation with exponentially shallower circuits compared to arithmetic-heavy approaches, effectively bypassing the Gibbs phenomenon.

6 Discussion & Conclusion

Our analysis demonstrates a clear separation between classical and quantum risk estimation regimes.

1. **Advantage:** The quantum quadratic speedup ($\mathcal{O}(1/\epsilon)$) is validated in the Classiq simulator. This advantage is most pronounced in high-precision regimes where classical Monte Carlo hits a "computational wall."

2. **Assumptions:** The advantage assumes efficient state preparation. The "Soft-CVaR" extension further suggests that by changing the mathematical definition of the risk function to be smooth, we can extract quantum advantage even earlier in the fault-tolerant era.

3. **Final Verdict:** While classical Monte Carlo remains efficient for rough estimates, IQAE combined with Bisection Search offers a superior scaling pathway for the high-precision demands of regulatory capital calculation.