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BIG QUANTUM HACKATHON QATAR 2025

QATAR'S FIRST GLOBAL QUANTUM COMPUTING HACKATHON

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TEAM #1: Oryqs

Constrained Portfolio Optimization

Qatar Development Bank x IBM

Working out the use case

Use case	Relevance for QBD + Impact for Investment Banking	Quantum improvement + Feasibility	Our expertise	1 day results	Total
Fraud Detection + Quantum Kernels	2	4	4	5	15
Risk Assessment + Quantum Amplitude Estimation (QAE)	4	3	4	3	14
Portfolio Optimization + Quantum Combinatorial Optimization	5	4	3	4	16
Predicting Index Pricing + Quantum Machine Learning (QML)	4	4	3	4	15

Business Case

QBD’s Current Challenges

- Best **combination** of **investments**.
- **Managing risk** while **maximizing return** under tight budget **constraints**.
- Delivering **personalized portfolio** recommendations for each client.

Struggles of classical methods

- Markowitz optimization is computationally expensive with **many assets**.
- **Constraints** make it a **combinatorial NP-hard problem**.
- Optimization for thousands of clients is **expensive**.

Model formulation

Portfolio optimization

Quadratic Constrained Ternary Optimization

$$\min_{x_i \in \{-1,0,1\}} \left[\lambda \overbrace{\sum_{ij=1}^{n} A_{ij}(t) x_i x_j}^{\text{Risk minimization}} - \overbrace{(1-\lambda) \sum_{i=1}^{n} b_i x_i}^{\text{Return maximization}} \right]$$

Risk aversion

Covariance matrix

Return expectations

Short $x_i = -1$

Hold $x_i = 0$

Buy $x_i = 1$

Constraints

$$\lambda = \frac{1}{2}$$

→

$$\min_{x \in \{-1,0,1\}^n} (x^T A x - b \cdot x)$$

$$\sum_{i=1}^{n} x_i = K$$

Portfolio position
=
Market confidence

Q~~U~~~~B~~O

Brute force classical solution → **Exponentially** many positions

Map to our solution

Binary encoding

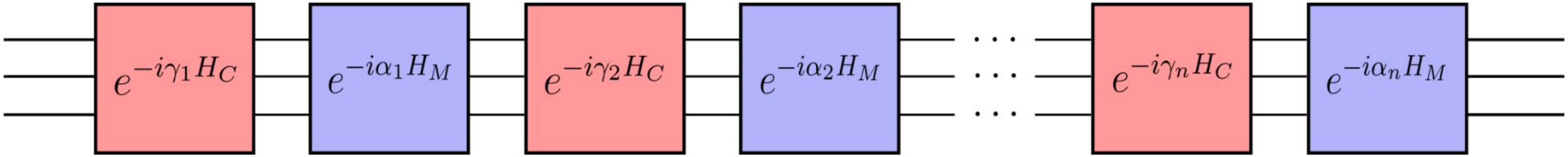
x_i	u_i^1	u_i^2
-1	1	-1
0	1	1
0	-1	-1
1	-1	1

$$\min_{x\in\{-1,0,1\}^n} \left(x^T A x + b\cdot x\right) = \min_{u\in\{-1,1\}^{2n}} \left(u^T B u + c\cdot u\right)$$

$$B = \frac{A}{4} \otimes \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \qquad c = \frac{b}{2} \otimes \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

Number of qubits = 2 x number of assets

Circuit explanation



Our innovation

- Combinatorial solution in **ground state** of **cost hamiltonian** H_C, reached by evolving from **mixing hamiltonian** H_M
- **Constraints** -> H_M as in: “Quantum walk-based portfolio optimisation. Quantum, 5, 513”
- Scaling issues in variational optimization in many layers -> **linear ramp ansatz** as in “Toward a linear-ramp QAOA protocol: evidence of a scaling advantage in solving some combinatorial optimization problems. npj Quantum Inf 11, 131 (2025)”.

Our proposition

QAOA

Typically explored for Near-term Quantum Computers

+ Well-**studied**

- **Unconstrained** (QUBO), limits relevance
- **Deep** circuits (pN^3)
- **Unpredictability** and **scaling issues** in training

QAOA-**Z**

Encoding **constraints** in the Mixing hamiltonian

+ Adapted to IBM Hardware
+ More **realistic** problem
+ Relying on **known** basis

- Still heuristic training
- Still deep circuits

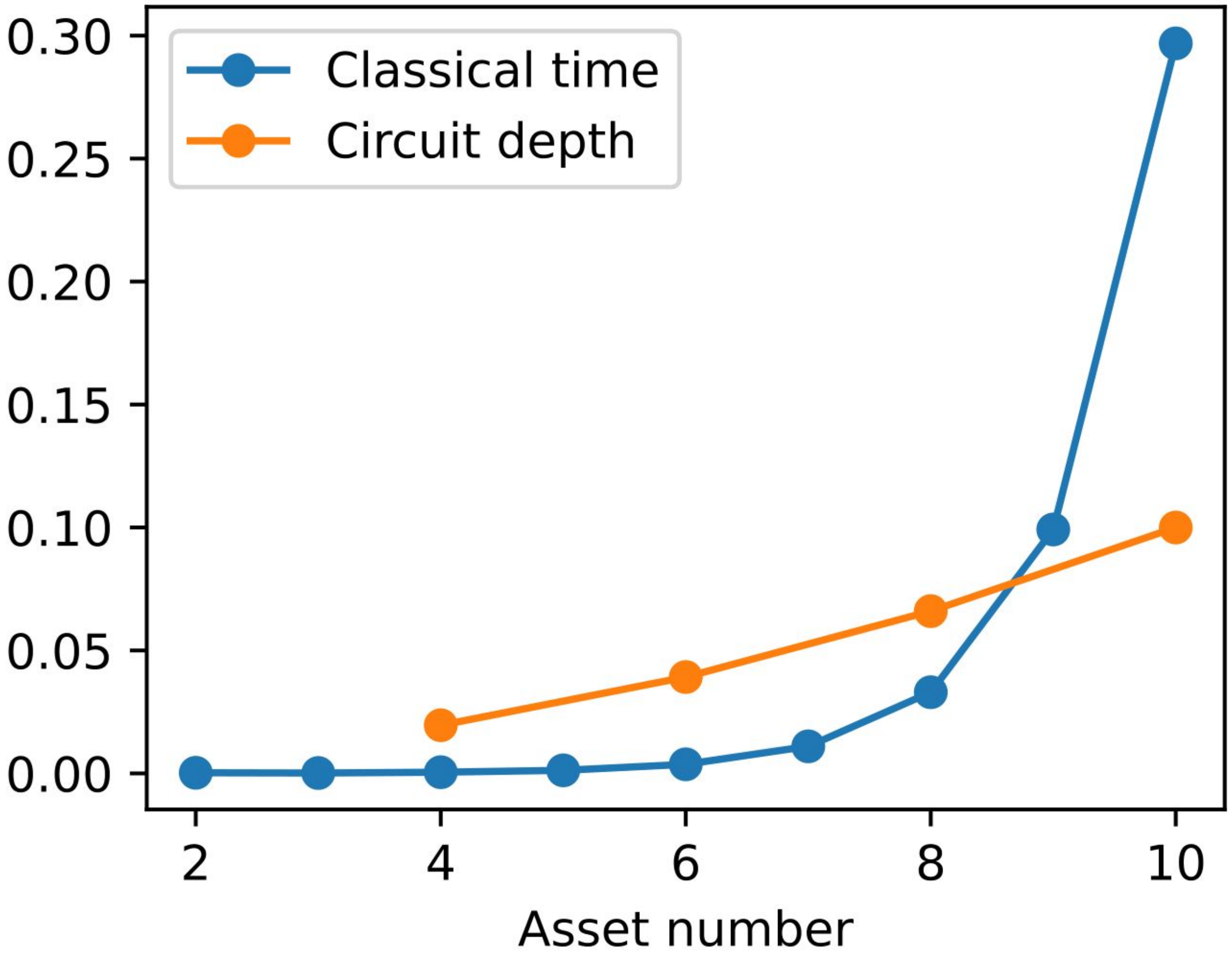
LR-QAOA-**Z**

Force **linear training schedule**
Parameters size : 2p -> 2 (slopes)

+ **Predictable** training
+ More **realistic** problem
+ Relying on **known** basis

- Still deep circuits

Better Scaling



Exponential runtime classical

vs

Qubic circuit depth

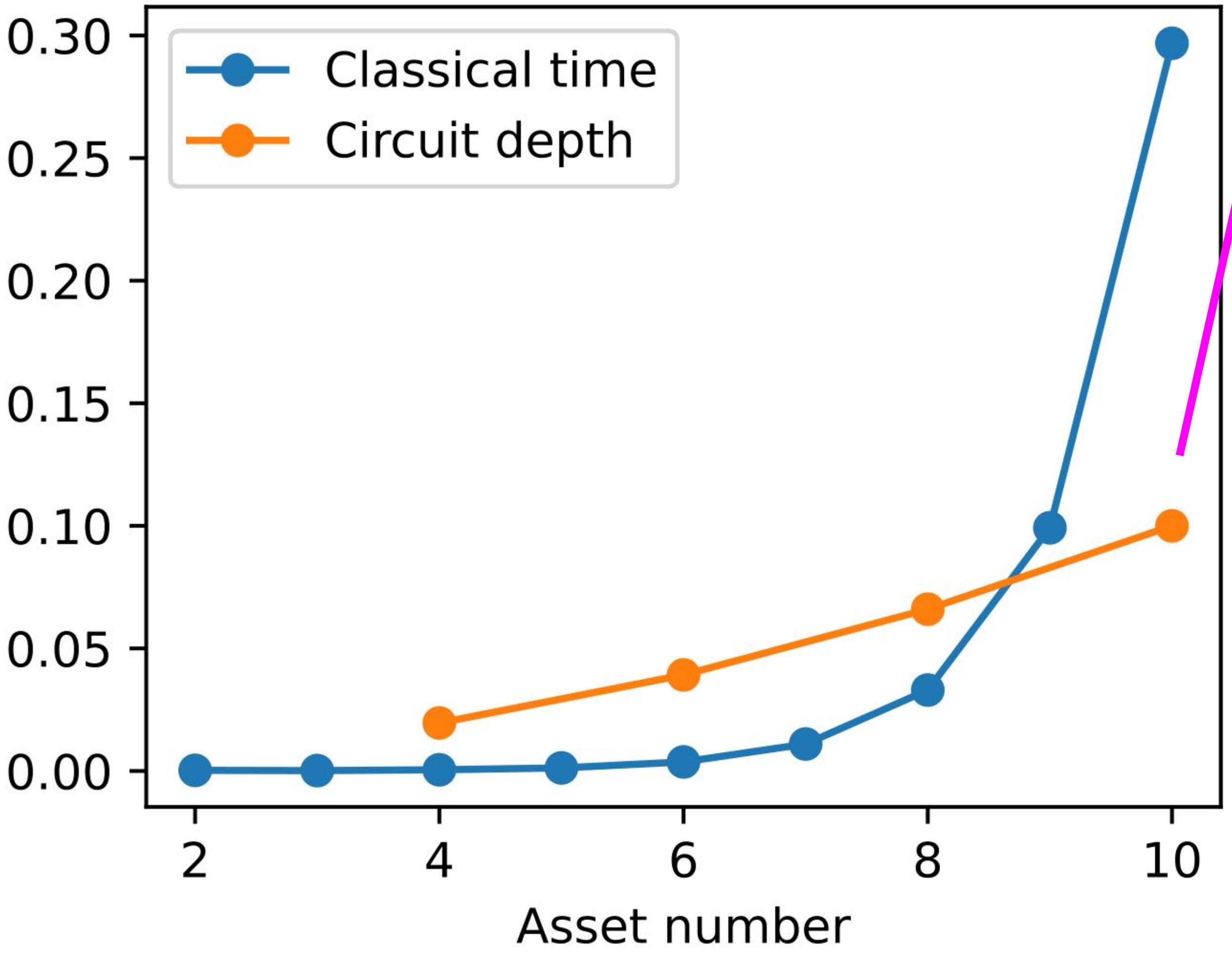
+ scale-independent training

With a **large** number of assets n

- Classical simulations become infeasible
- Quantum simulations still scale properly (pn^3)

Better Scaling

hardware - x10 times more



Exponential runtime classical

vs

Qubic circuit depth

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With a **large** number of assets n

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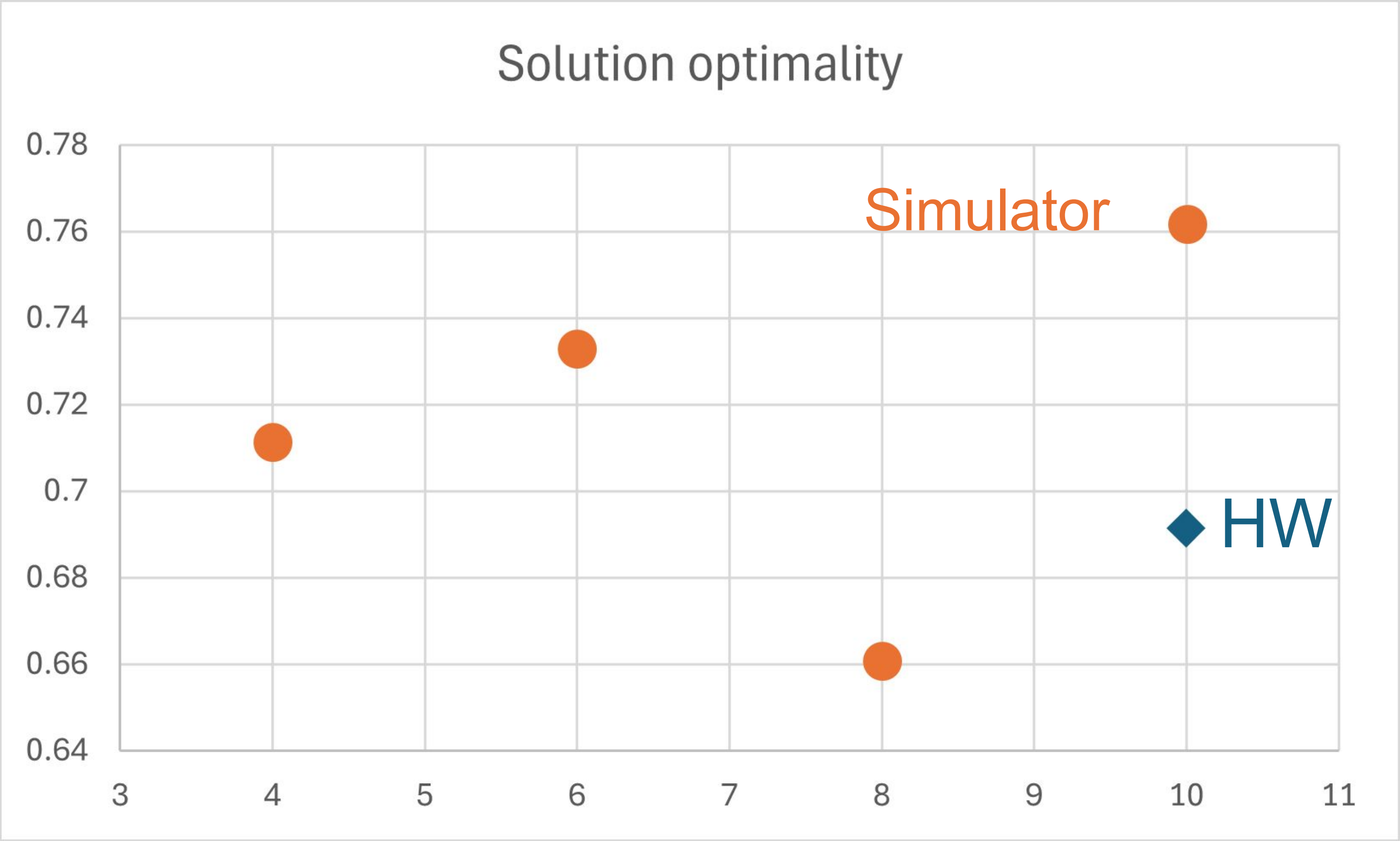
Comparable Quality

Optimality: (quantum-best) / (worse-best)



Run on **IBM** cloud Simulators and **Hardware** (up to 40 qubits):

Up to **70%** solution optimality, comparable to literature

Summary

- Novelty: combined improvements of routines
- Runtime advantage with polynomial scaling
- Comparable Quality - up to 70%

Next steps

- Optimise training schedules
- Add new types of constraints
- Explore theoretical bounds on performance
- Extensive study with real IBM quantum hardware, up to 127 qubits

IBM **Quantum**

THANK YOU!

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