

Fraternité





Experimentation Campaign on QPUs Using Q-score Metric

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4 June 2024





















Q-score: A Broader View





> Q-score Highlights:

- Q-score, introduced by Atos in 2021
- Quantifies the performances of quantum devices in solving specific problems
- ➤ Unlike existing metrics, Q-score is application-oriented and provides a scalable way to assess QPU capabilities
- > Q-score allows us to compare the true performances of various QPUs

➤ Application-Driven Metrics:

- Q-score methodology covers not only gate-based QPUs but also analog simulators and quantum annealers
- Application-driven metrics like Q-score provide transparency and guide users and manufacturers

> Future Prospects:

- > Expect more Q-score variants for different use cases beyond optimization problems
- Collaboration with international scientists will further refine and expand the Q-score family
- Q-score maturity and its widespread adoption open the door to discussions about benchmarking standardization



Quantum Computing

Quantum Engineering

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Benchmarking Quantum Coprocessors in an Application-Centric, Hardware-Agnostic, and Scalable Way

SIMON MARTIEL[®], THOMAS AYRAL[®], AND CYRIL ALLOUCHE
And Quantum Laboratory. 95877 Les Clayes-sous-Rois. France















Fast-Track BACQ initiative





> Fast-Track Quantum Computing Benchmarking Initiative:

- ➤ A collaborative effort among quantum computing industry leaders
- ➤ Objective: Conduct a comprehensive measurement campaign on existing Quantum Processing Units (QPUs) using the Q-score metric
- Significance: Marks a pivotal moment in quantum computing evaluation and benchmarking
- > Broad Collaboration
- > Open Collaboration
- > Future and Impact:
 - > Fast-Track stands as evidence of collaborative innovation in quantum computing
 - Advanced partnerships and open contributions will shape the future of quantum computing benchmarks
 - ➤ Fast-Track's success leads to an extension of our tests, deepening our understanding of quantum computer benchmarking

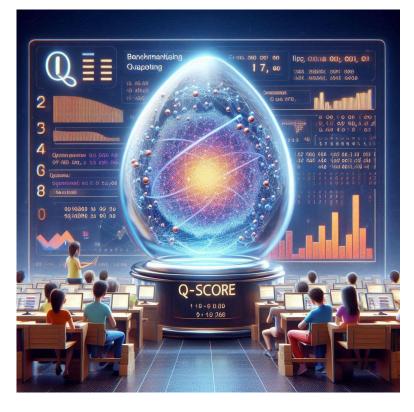


Illustration generated by IA (Dall-E 3)













Q-score experimentation Campaign

> **IQM**:

- Qubit technology: Superconducting
- Presented by Jami Rönkkö (10 mins / remote)
- Q-score/Max-Cut With QAOA

> Pasqal:

- Qubit technology: Neutral Atom
- Presented by Louis-Paul Henry (10 mins / In-person)
- Q-score/Max-Cut with Maximum Independent Set (MIS)

> Quandela:

- Qubit technology: Photonic
- Presented by Vassilis Apostolou (10 mins / remote)
- Q-score/Max-Cut with Variational Quantum Eigensolver (VQE)

> TNO:

- Research institute: Toegepast Natuurwetenschappelijk Onderzoek
- Presented by Ward van der Schoot (10 mins / remote)
- Q-score/Max-Cut implementation on D-wave





























Experimentation Campaign on QPUs Using Q-score Metric

Jami Rönkkö (IQM)

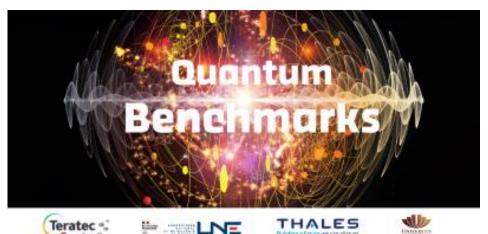
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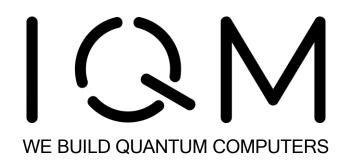












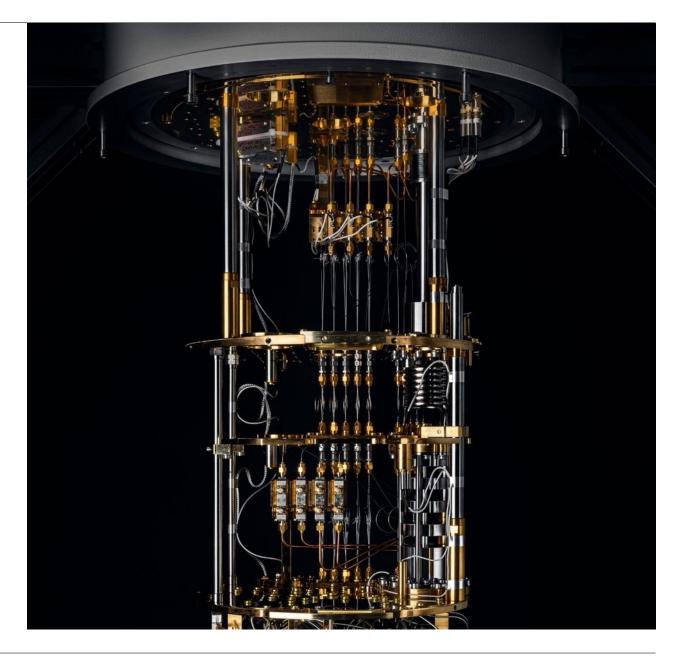
Q-score at IQM:

Results and Suggestions

Jami Rönkkö

IQM Quantum Computers

www.meetiqm.com

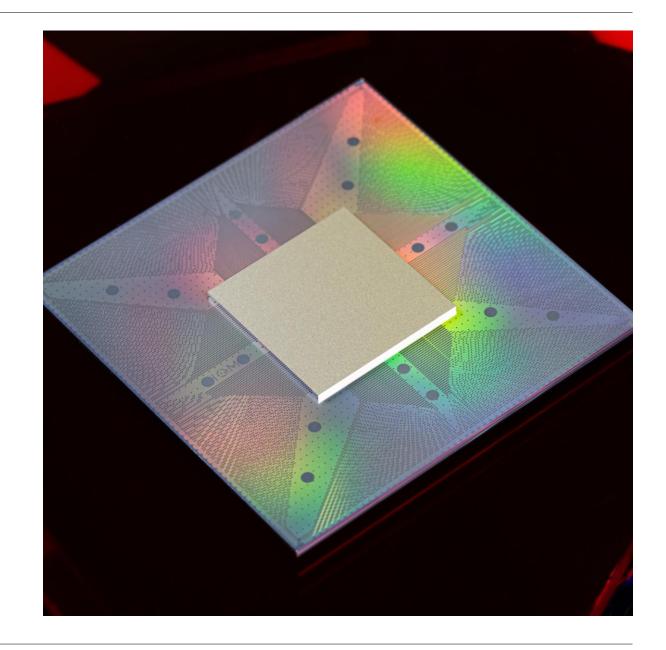


Contents

1. Preliminaries

2. Results

3. Suggestions



1. Preliminaries: Q-score definition

I. Definition

$$\beta(n) = \frac{C(n) - \frac{n^2}{8}}{\lambda n^{3/2}} \qquad \beta(n) = \frac{C(n) - \frac{(n-1)n}{8}}{\lambda n^{3/2}}$$

II. Number of shots: 2048 20 000

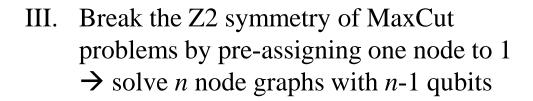
III.Number of instances: 100 (we use 100 instances though more might be needed to get reliable averages)

Martiel, Simon, Thomas Ayral, and Cyril Allouche. *IEEE Transactions on Quantum Engineering* 2 (2021): 1-11.

1. Preliminaries: algorithmic tricks

I. Readout error mitigation

II. For ansatz layer depth p=1 one can use classically computed optimal angles \rightarrow no need for quantum-classical loop for finding angles



Bravyi, Sergey, et al. *Physical review letters* 125.26 (2020): 260505.



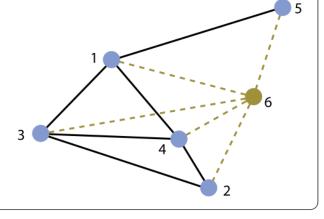
Theorem 1. For QAOA with p = 1, for each edge $\langle uv \rangle$,

$$\langle C_{uv} \rangle = \frac{1}{2} + \frac{1}{4} (\sin 4\beta \sin \gamma) (\cos^{d_u} \gamma + \cos^{d_v} \gamma) - \frac{1}{4} (\sin^2 2\beta \cos^{d_u + d_v - 2\lambda_{uv}} \gamma) (1 - \cos^{\lambda_{uv}} 2\gamma),$$
(14)

where $d_u + 1$ and $d_v + 1$ are the degrees of vertices u and v, respectively, and λ_{uv} is the number of triangles in the graph containing edge $\langle uv \rangle$.

Wang, Zhihui, et al. Physical Review A 97.2 (2018): 022304.

Figure 12 Maxcut problem for six nodes. Node 6 is a fictitious qubit in |1\) state while rest are physical qubits. Solid lines represent physical couplings while dashed lines fictitious couplings

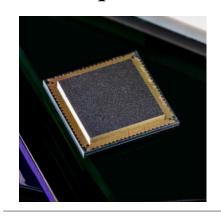


Rönkkö, Jami, et al. EPJ Quantum Technology 11.1 (2024): 32.

2. IQM Quantum Computer - Garnet

20 qubit superconducting data qubits and 30 coupler qubits

Cloud access at: https://resonance .meetiqm.com/





TOPOLOGY

Square-lattice topology

QUBITS

20

NATIVE GATES

barrier, cz, measure, prx

MAXIMUM CIRCUITS / MAXIMUM SHOTS PER JOB

200 / 20000

MEDIAN T1

42.23 µs

MEDIAN T2

 $7.72 \, \mu s$

MEDIAN SINGLE-QUBIT GATE FIDELITY

99.92 %

MEDIAN CZ GATE FIDELITY

99.41 %

Gate times:

cz : 48 ns

prx : 20 ns

Sub-10 ns prx gates being implemented at the moment: Hyyppä, Eric, et al. *arXiv preprint*

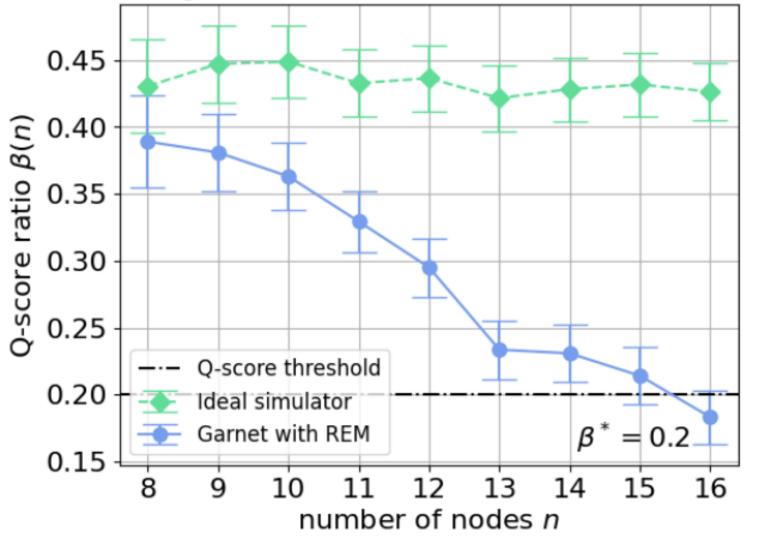
arXiv:2402.17757 (2024).

2. Results

$$Q$$
-score = 15

- seed = 1
- 100 instances
- 20 000 shots

Solving MaxCut with QAOA (with 1 virtual node)



3. Suggestions for modifying Q-score

Make the benchmark even more application centric

- 1. Look for best solution, not for average
 - this is what real users are interested in
- 2. Demand reporting of time-to-solution or alternatively total shot budget
 - time to solution could be in terms of flops
- 3. Compare to best classical polynomial-time approximation algorithm (Goemans and Williamson) instead of random sampling
 - e.g. for how many nodes one can get as good solution as G&W and how long/many flops did it take
- 4. Clarify whether default QAOA should be used or if iterative (hybrid) versions of QAOAs are allowed. These will lead to higher Q-scores at the cost of extra classical processing.



Experimentation Campaign on QPUs Using Q-score Metric

Louis-Paul Henry (Pasgal)

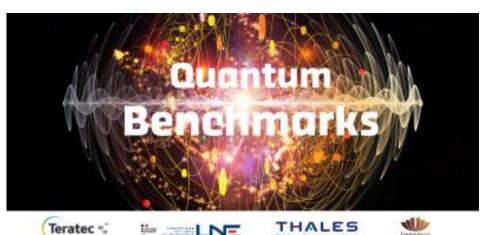
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Optimization benchmarks for neutral atom QPUs

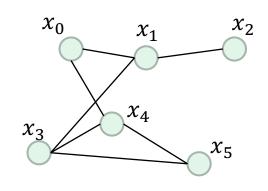
Extending the Q-Score definition

Louis-Paul Henry

The Max-Cut Problem



The QUBO formulation for the Max-Cut problem



$$x_i = \{0,1\}$$

The MAX-CUT set is found as:

$$\underset{\{x_i\}}{\operatorname{argmin}} \left(-\sum_{i \in V} N_i x_i + \sum_{i,j \in E} x_i x_j \right)$$

 $N_i = Numbers of neighbours$

Any QUBO matrix can be translated into a Weighted Max-Cut instance

Barahona, Francisco, Michael Jünger, and Gerhard Reinelt. "Experiments in quadratic 0–1 programming." *Mathematical Programming* 44.1-3 (1989): 127-137.

Q-score (for Max-Cut)



Associated cost function
$$(z_i \in \{+1; -1\})$$

 $C(z_1, ..., z_N) = \sum_{(i,j) \in E} z_i z_j$

Max-Cut for Erdös-Renyi graphs of size N

Average cost for a random cut¹:

$$Rand(N) \approx \frac{N^2}{8}$$

Optimal cost:

$$Opt(N) \approx \frac{N^2}{8} + \lambda N^{\frac{3}{2}} \left(\lambda \sim 0.178 \right)$$

Any algorithm such that Algo(N) > Rand(N):

$$\lim_{N\to\infty} Algo(N)/\operatorname{Opt}(N)=1$$

[1] A. Dembo, A. Montanari, S. Sen, "Extremal cuts of sparse random graphs", The Annals of Probability, vol. 45, no. 2, pp. 1190 –1217, 2017

Q-score

Refined approximation ratio:

$$\beta(N) = \frac{Algo(N) - Rand(N)}{Opt(N) - Rand(N)} = \frac{Algo(N) - \frac{N^2}{8}}{\lambda N^{\frac{3}{2}}}$$

One expects $\beta(N)$ to decrease as $N \to \infty$

Q-score defined as

$$Qs(Algo) = \max\{N \mid \beta(N) > 0.2\}$$

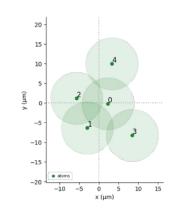
Analog Quantum Computing with neutral atoms

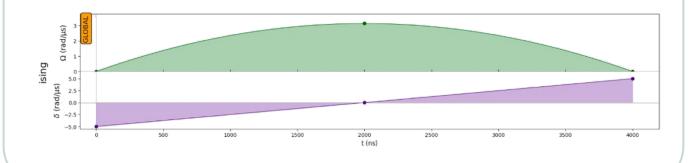


Native Hamiltonian: Ising

$$H_{Ising}$$

$$= \frac{\hbar\Omega(t)}{2} \sum_{i=1}^{N} \hat{X}_{i} - \hbar\delta(t) \sum_{i=1}^{N} \hat{n}_{i} + \sum_{i < j} \frac{C_{6}}{|r_{i} - r_{j}|^{6}} \hat{n}_{i} \hat{n}_{j}$$





Native Problem : Maximum Independent Set (MIS)



Each node has a label $n_i = \{0; 1\}$

Space of solutions $S = \{0, 1\}^N$ and $|S| = 2^N$

Associated cost function

$$\label{eq:continuous} \begin{array}{l} C(n_1,\dots,n_N) = -\sum_{i=1}^N n_i + U \sum_{(i,j) \in E} n_i n_j \end{array}$$
 with $U \gg 1$

Extension to Q-score



Constrained optimization

- MaxCut is unconstrained optimization
 ⇒ « easier » to approximate
- Sampling/exploring constrained space is typically hard

$$\Rightarrow$$
 typically $Random(N) \rightarrow 0$

Example 1 : MIS

$$\underset{n \in \{IS\}}{\operatorname{argmax}} \sum_{i=1}^{N} n_i$$

• Example 2 : weighted-MIS $(\{w_i\} \in \mathbb{R}^N)$

$$\underset{n \in \{IS\}}{\operatorname{argmax}} \sum_{i=1}^{N} w_i n_i$$

Extended Q-score

- Scaling of naïve algorithm (Random, Greedy, ...) Naive(N)
- Scaling of best algorith (State-of-the-art, theoretical, ...)

Extended approximation ratio

$$\beta(N) = \frac{Algo(N) - Naive(N)}{Best(N) - Naive(N)}$$

Extended Q-score defined as

$$Qs(Algo) = \max\{N \mid \beta(N) > \alpha\}$$

Where the threshold α can be application specific

Method

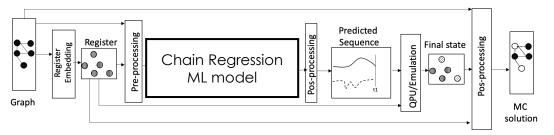


Properly accounting for cost

- Cost of classical preprocessing
- Cost of optimizating parameters
 - QOAO parameters
 - Register embedding (n. atoms, ...)
 - Pulse shaping (analog, ...)
- Sampling cost (number of shots)
 - $N_{shots}^{final} \sim (overlap\ of\ state\ with\ sol.)^{-1}$
 - $N_{shots}^{total} \sim N_{shots}^{final} + N_{shots}^{optim}$ $\Rightarrow \text{Trade off}$

ML-assisted pulse shaping and register embedding

- The goal: $N_{shots}^{total} \sim N_{shots}^{final} + N_{shots}^{optim}$
- <u>The idea</u>: Train a model that outputs one or more
 « good enough pulse », given a graph and a Register



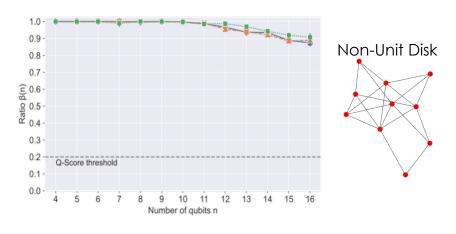
- Input parameters:
 - graph properties: order, size, density, min/max/av.
 neighbourhood size
 - Register: min/max/av. distance (in µm) between connected/disjoint nodes
- Supervized training (but dataset was not optimal)

TQCI 2024, Reims

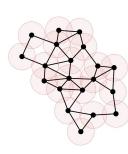
Results

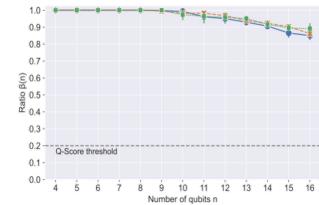


MaxCut

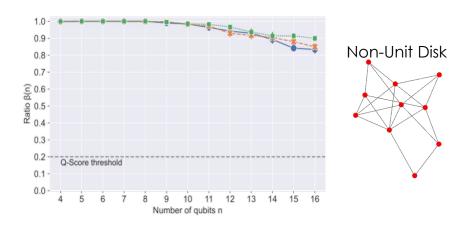


Unit Disk

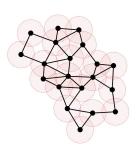


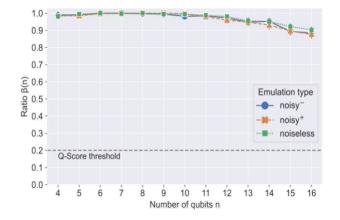


MIS



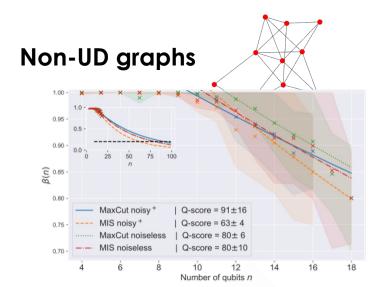
Unit Disk

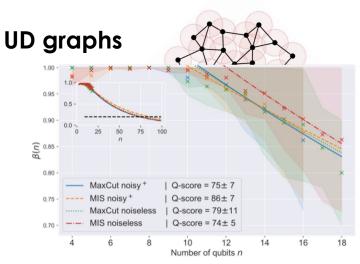




Results and conclusion







Conclusion

- We could solve MaxCut and MIS problem even on non-UD graphs
 - Better results for MaxCut on non-UD graphs
 - Better results for MIS on UD graphs
- The supervised ML can learn how to predict good pulses for both graph problems
 - Not dependent on the graph size/order
 - Need a "good" training data set
- Embedding Strategies could improve for some graph classes

Persepectives

- Refine the model
 - Improve training dataset
 - Train on (mixed emulation-)QPU results
- Extend to other algorithms and/or problems



Experimentation Campaign on QPUs Using Q-score Metric

Vassilis Apostolou (Quandela)

4 June 2024















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Q-score using Single Photons and **Linear Optics**

Teratec TQCI Benchmark

Quandela

Ana Filipa Carvalho – Quantum Applications Engineer June 2024



\mathcal{C}

Quandela's implementation and results for Q-score: Index

- Q-score metric
- Photonic Quantum Computing & Information
- Our algorithm Why not QAOA?
- Results



Atos' Q-score metric

Benchmarking method "application-centric, hardware-agnostic and scalable to quantum advantage"

"The Q-score measures the maximum number of qubits that can be used effectively to solve the Max-cut combinatorial optimization problem".

Conditions for a proper benchmark:

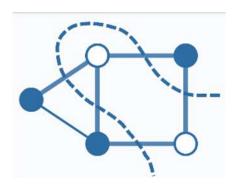
- 1. Application-centric
- 2. Hardware-agnostic
- 3. Scalable

Q-score measures the maximum number of quantum bits that a quantum computer can use to solve a combinatorial optimization problem—the Max Cut problem—significantly better than a classical random algorithm.

Ç

Atos' Q-score metric Max-cut problem

- Graph G(V, E) of V vertices and E edges.
- Goal: find a partitioning (cut) of V into V_1 and V_2 s.t the number of edges not belonging to either of the induced subgraphs $G_1(V_1, E_1)$ and $G_2(V_2, E_2)$ is maximum.
- The set of edges $E/(E_1 \cup E_2)$ is called a cut, so MAXCUT is simply the problem of finding a cut of maximum cardinality.
- NP-complete

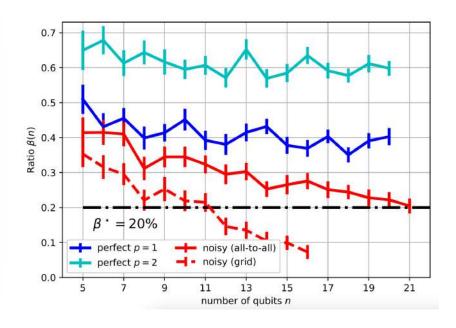


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Atos' Q-score metric Quantum algorithm for the Max-cut problem

Core of the benchmarking technique:

- 1. Fix some p.
- 2. Work with QAOA for MAXCUT on random graphs of n vertices, whose average number of solutions is known.
- 3. An ideal quantum device can solve with accuracy a% on average this problem.
- 4. Choose an accuracy b% < a% and define Q-score as the largest n for which the noisy quantum device can solve MAXCUT using QAOA on random graphs with accuracy b%.



Optical Quantum computing Quandela's vision

MAIN INGREDIENTS

Type

Discrete variables: single photons

Encoding

Dual rail: integrated photonic

Time: fibre loops & delay

KLM: linear optical circuits – NISQ

(up to tens of qubits)

Scheme MBQC inspired: operation on cluster states, fusion gates –

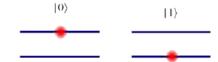
towards fault-tolerant

Approach

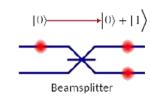
Efficient modules interconnected by ultra-low loss fibre links

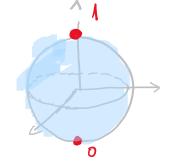
PHOTONIC QUBITS

Qubit encoding

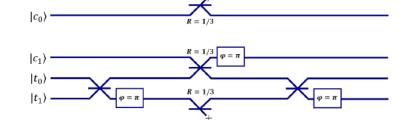


1-qubit gates





2-qubit gates





The Knill–Laflamme–Milburn (KLM) scheme Dual rail encoding

- We could end up detecting 2 photons in the modes of the qubit 0...
 - But this can't be interpreted as a qubit output!
 - When this happens, we just ignore the run and try again \rightarrow post-selection
 - Thus 2-qubit operations are probabilistic (KLM-scheme)
- KLM is a problem for the <u>scalability</u> of the approach
 - E.g. Try performing 50 operations each of which succeeds with say probability ½...
 - Ultimately, we will need a different model of computing a more clever way to instantiate qubits with photons

The best (known) success probability of a CNOT-gate is 1/9 (post-selected), 2/27 (heralded)



VQA

Max-Cut problem:

Low level analysis of photonic Implementation

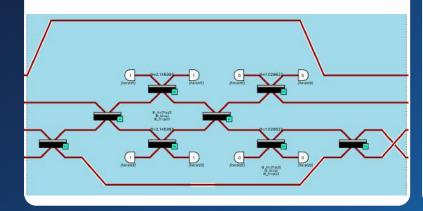
Variational Quantum Algorithms

Naive qubit translation

Variational Quantum Eingensolver – VQE

Quantum Approximate Optimization Algorithm – QAOA

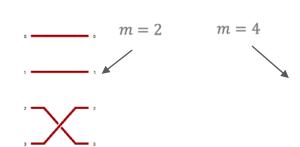
Variational Quantum Linear Solver - VQLS



Hyper Encoding scheme: Qubit Logic On Qudits (QLOQ)

Deterministic gates by different spatial encoding scheme.

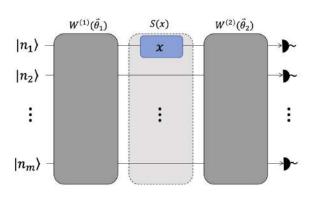
KLM scheme with QLOQ encoding.



Photonic VQA [1], VBS

VQ circuit designed as an equivalent to neural networks;

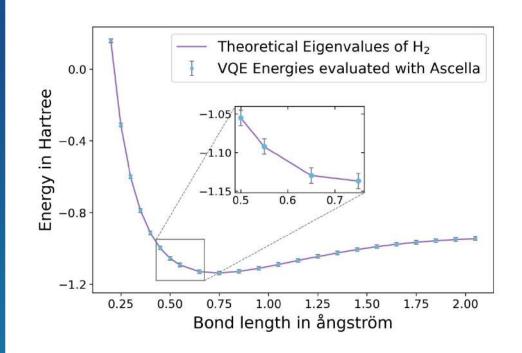
Data encoding operation S(x)Parametrized operations $W(\Theta)$: train over Θ



Variational Quantum Eigensolver: Better tailored to photonic hardware

Goal:

Find the ground state energy of a molecule given the coordinates of its nuclei. An example in Quandela's toolbox is the H_2 molecule.



Variational Quantum Eigensolver: Better tailored to photonic hardware

Goal:

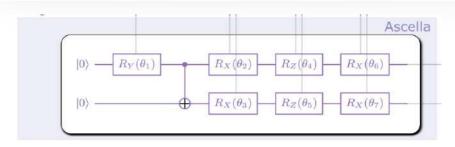
Find the ground state energy of a molecule given the coordinates of its nuclei. An example in Quandela's toolbox is the H_2 molecule.

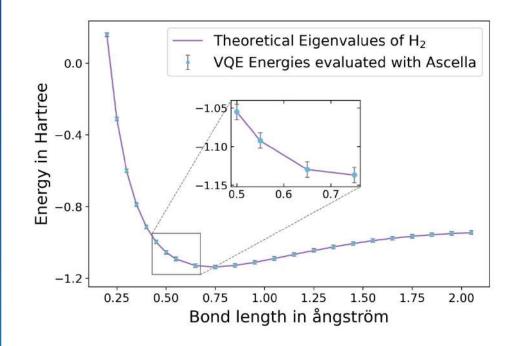
Step 1:

We prepare an ansatz for the quantum state with a circuit that has variational parameters.

Step 2:

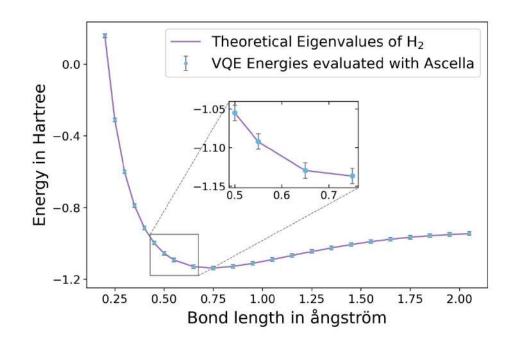
The chemical problem is converted into a qubit Hamiltonian. Our circuit measures this qubit Hamiltonian and adds up averages of each measurement to gain an approximation of the ground state.





Variational Quantum Eigensolver: Better tailored to photonic hardware

Find the ground state energy of a molecule given the coordinates of its Goal: nuclei. An example in Quandela's toolbox is the H_2 molecule. Classical processor Gradient descent Build expectation Compute loss for feedback values from control samples $\sum \langle \psi(\theta) | \hat{H}_i | \psi(\theta) \rangle$ $\langle \psi(\theta)|\hat{H}_i|\psi(\theta)\rangle$ $d_{\theta} \left(\sum \langle \psi(\theta) | \hat{H}_{i} | \psi(\theta) \rangle \right)$ $\theta^{ ext{updated}}$ Ascella $R_X(\theta_7)$





Qubit Logic On Qubits (QLOQ) encoding: Core concept

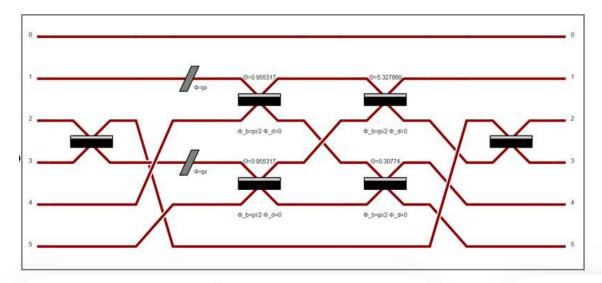
Divide a circuit into groups of qubits and map each group to a physical qudit.



Qubit Logic On Qubits (QLOQ) encoding: Core concept

Divide a circuit into groups of qubits and map each group to a physical qudit.

Advantage #1: Entagling gates between qubits in the same group become local (single-qudit) operations!



 ${\rm Knill\ CNOT} \\ ^{2}/_{27}\ {\rm success\ probability\ with\ 2\ heralding\ photons\ needed}$

Local QLOQ CNOT
Deterministic with no heralding photons needed



Faster optimization:

Conditional Value at Risk (CVaR) for faster convergence

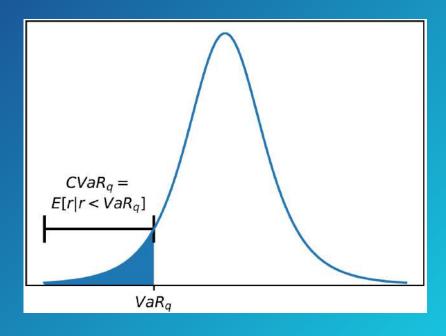
Q: How to implementing a CVaR approximation to Generic VQE for QUBO? The user essentially defines a tail end to their probability distribution, a variable we call α .

Main points:

- Allows to find results faster.
- o It has the same qubit number requirements as Generic VQE.
- Resilient to noise, both quantum and statistical unlike the generic version --> less significantly less shots per run and indicating it will scale as our hardware grows.

 $\alpha = 1 \rightarrow \text{runs generic VQE on a standard optimization problem.}$

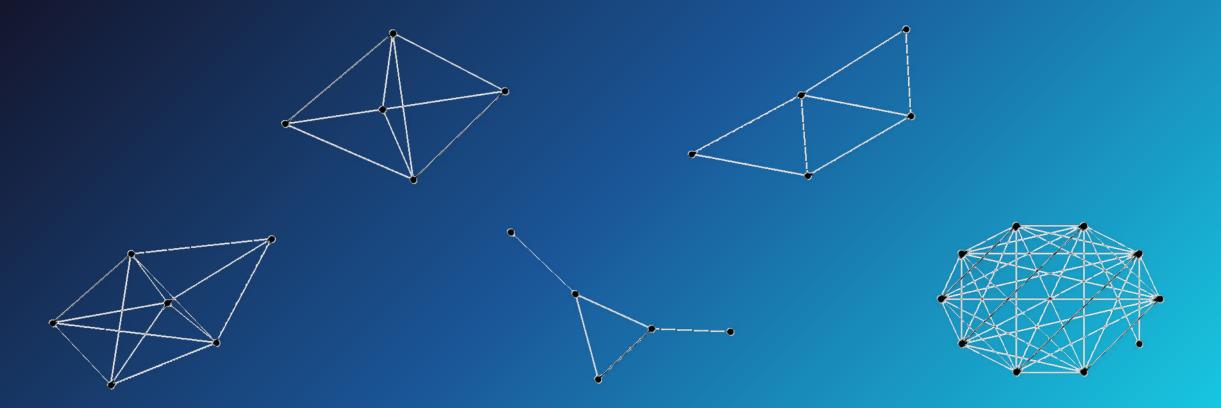
 α < 1 \cdots takes a segment of the probability distribution, quicker convergence and reaches the optimal bitstring with higher accuracy.



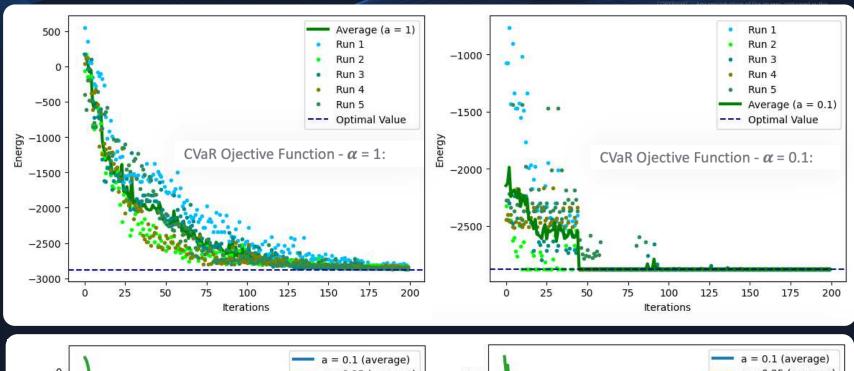
\mathcal{C}

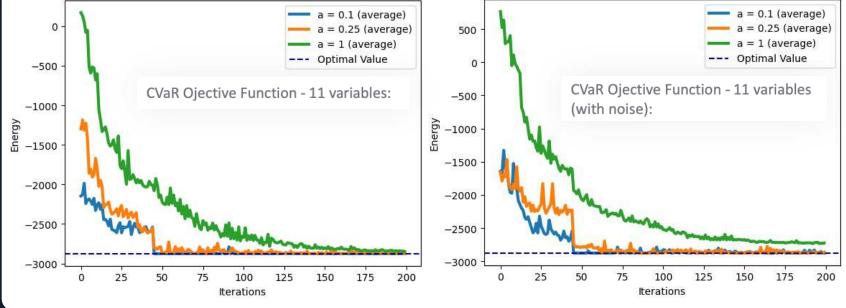
Numerics:

Implementation and results



Results
CVaR-VQE versus VQE for
Applications & Noisy Environment





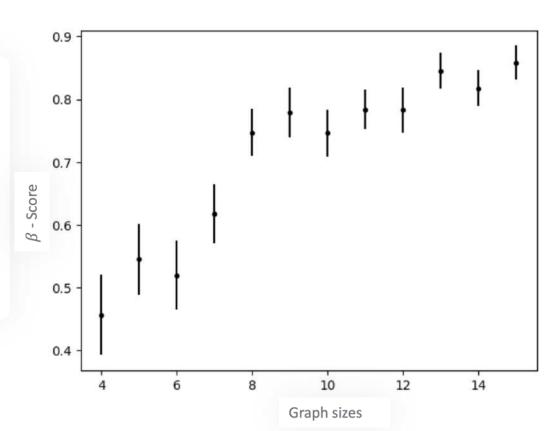
Q

Atos' Q-score Results with CVaR-VQE implemented in Perceval

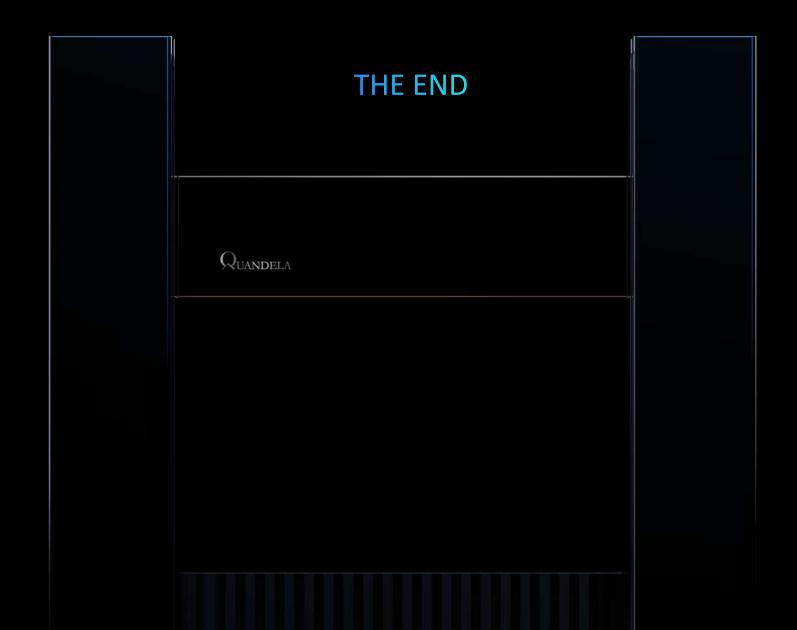
Results for Q-score with CVaR-VQE tailored for photonic technologies with QLOQ encoding.

Maximum size tested: 15 nodes.

Difficulty for larger tests: simulation runtime.









Experimentation Campaign on QPUs Using Q-score Metric

Ward van der Schoot (TNO)

4 June 2024



















Showing the strength of Q score as a framework

Ward van der Schoot MMath



Quantum at TNO

- The Netherlands Organisation for applied scientific research
- Mission:
 - To generate innovative solutions with provable impact for a safe, healthy, sustainable and digital society in the Netherlands and beyond.
- Quantum applications at TNO. Goal:
 - To enable practical implementation of relevant applications on current and/or near term quantum devices.
- Quantum benchmarking at TNO:
 - Goal:
 - Find the perfect device for a given application. Not for ourselves, but for industry
 - Considered many different application-level benchmarks
 - Focus on Q-score

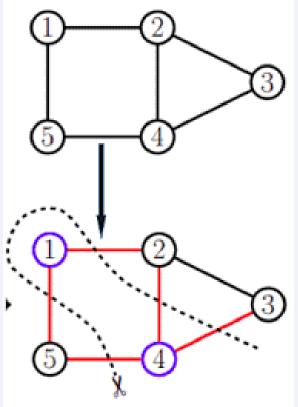




Original Q-score by Atos

 Largest problem size N for which a device significantly outperforms a random algorithm at solving the Max-Cut problem

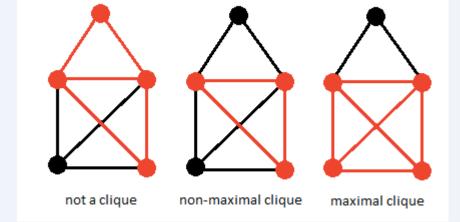
- Applicable on gate-based as well as annealing-based devices
 - Depends not only on the device
 - Also on the used algorithm, optimisations and resources





Extending Q-score framework: Q-score Max-Clique

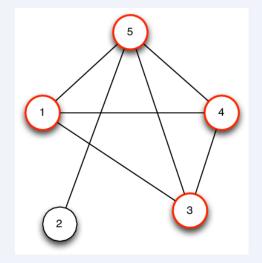
- Questions about the Q-score:
 - 1. Why do we specifically use the Max-Cut problem?
 - 2. What about other devices, such as photonic quantum computers?
- Q-score Max-Clique
 - Q-score with the Max-Clique problem
 - Find the largest clique: complete subgraph in G
 - Consider $\left(N, \frac{1}{2}\right)$ Erdös-Rényi graphs
 - Keep time constraint and optimisation as degrees of freedom



Q-score can be seen as a benchmarking framework with various degrees of freedom



Q-score Max-Clique



- 1. For increasing N, do the following steps:
- 2. Pick a collection of graphs of size *N*
- 3. Run a Max-Clique algorithm on each graph and compute average clique size C(N)
- 4. Check whether clique size is 'good': $\beta(N) = \frac{C(N) C_{rand}}{C_{max} C_{rand}} = \frac{C(N) 1.6416325}{2 \ln(N) 1.6416325} > \beta^* = 0.2$
- 5. Q-score Max-Clique is highest N satisfying this
- How do we estimate the max and random clique size C_{max} and C_{rand} ?
- Random clique size: Adding nodes randomly until no clique yields $C_{rand} = \sum_{i=0}^N i(1-p^i)p^{0.5i(i-1)} \approx 1.6416325$
- Max clique size: Literature study plus quantum and classical brute force suggest $C_{max} = 2\ln(N)$

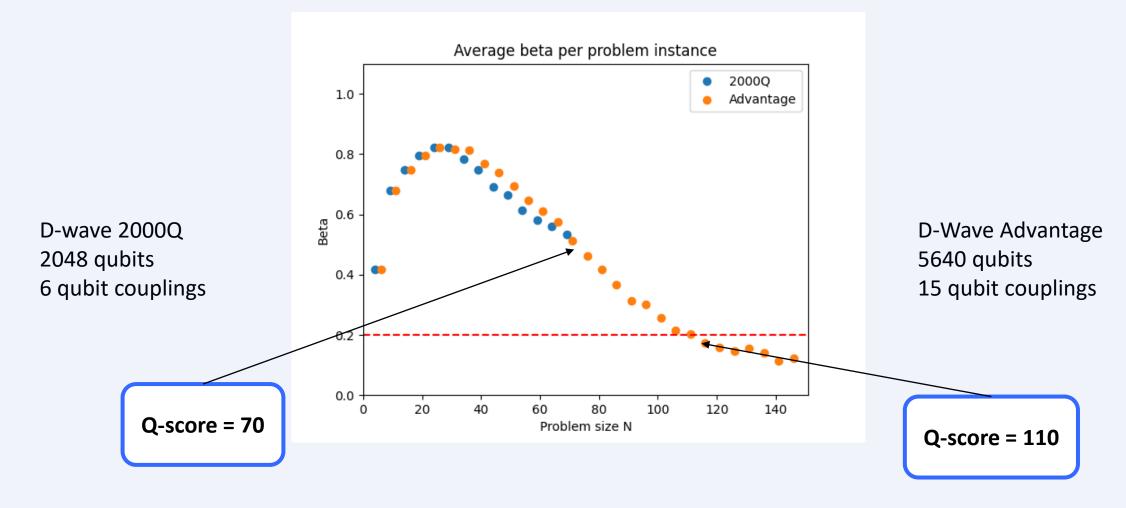


Experiments

- Calculate Q-score Max-Clique for following solvers
 - Quantum gate-based hardware
 IBM Guadalupe, Quantum Inspire Starmon-5
 - Quantum annealing hardware D-Wave Advantage, D-wave 2000Q
 - Quantum photonic hardware Quandela
 - Quantum photonic simulator Xanadu
 - Classical algorithms
 Simulated annealing, Tabu search
 - Hybrid quantum-classical solvers
 D-wave hybrid solver
- Extra constraints for specific metric instantiation:
 - Maximum calculation time: 60 seconds
 - Use out-of-the-box solvers:
 - Standard parameters
 - No extra optimisation allowed



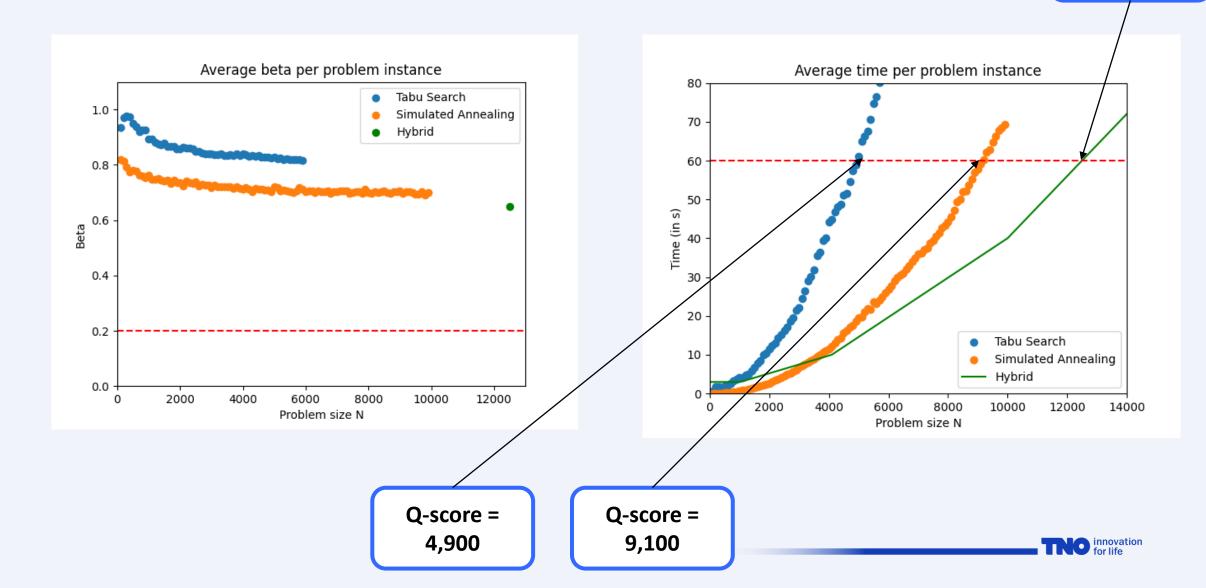
Q-score Max-Clique Annealing Hardware





Q-score Max-Clique Classical & Hybrid Solvers

Q-score = **12,500**



Results

Approach	Q-score
1. Tabu search	4,900
2. Simulated annealing 9,100	
3. D-Wave Advantage	110
4. D-Wave 2000Q	70
5. Hybrid annealing solver	12,500
6. Quantum Inspire Starmon-5	5*
7. IBM Guadalupe	≥5*
8. Quandela Ascella	3
9. Simulated gate-based 13*	
10. Simulated photonic-based	20*

• * = more than 60 seconds used



Conclusions

- Q-score yields a benchmarking framework to benchmark (quantum) devices in many ways:
 - Problem
 - Resources (time, optimisation, ...)
- This work: Q-score Max-Clique
 - Allowing native solution for photonic quantum hardware
- Goal:
 - Suite of metrics with plug-and-play degrees of freedom
 - More degrees of freedom, e.g., KPIs (time, energy, accuracy, problem size, ...)
 - See our talk later today Quantum Application Score (Koen Mesman)
 - Matching between application(s) and device(s)



Thank you

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Égalité Fraternité





Thank you for your attention

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4 June 2024



















