L3

Overview of different QC approaches

Göran Wendin
Chalmers

- Superconducting, trapped ions, semiconductors
- QC types (digital, analogue, adiabatic, annealing)
- Hybrid HPC+QC systems
- How the non-QC-expert end-user will benefit.

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Quantum computer architectures

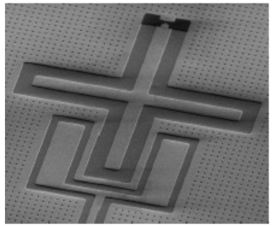
Superconducting

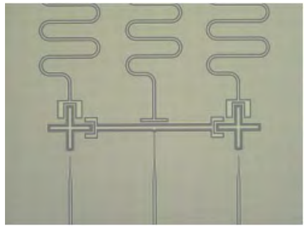
Ion traps

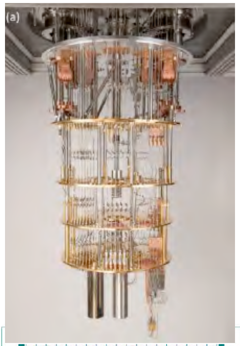
Neutral atoms

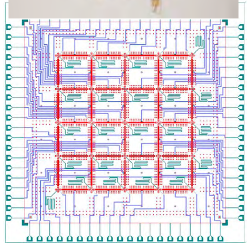
Semiconductor

Photonic

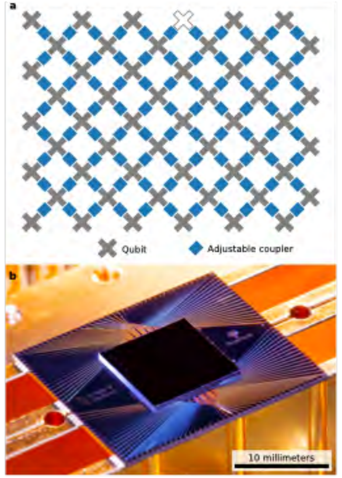




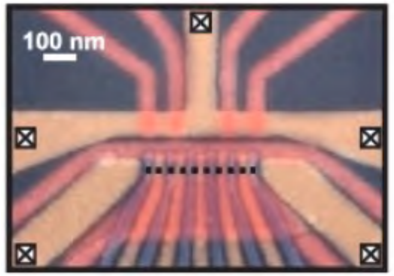


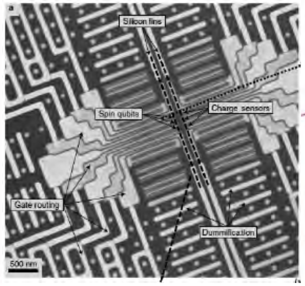


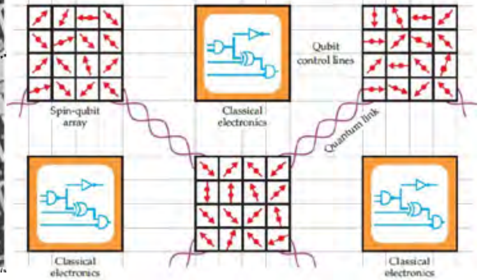
Chalmers 25q

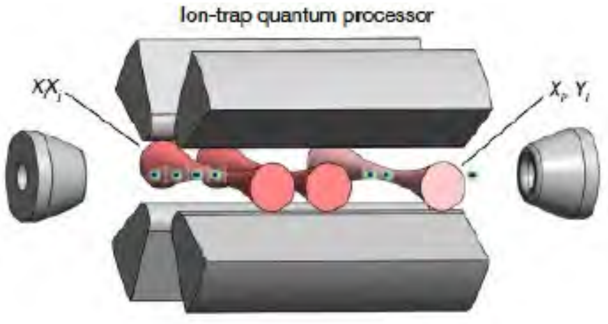


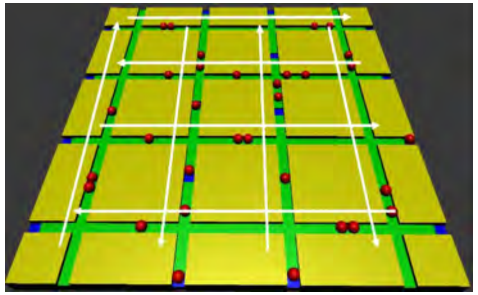
Google 53q
Sycamore

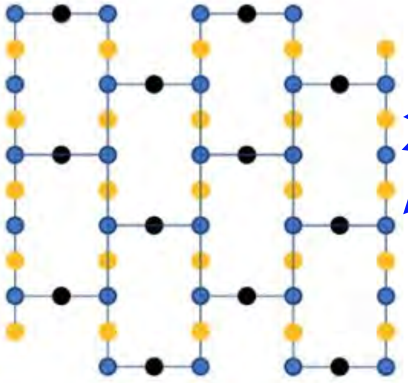






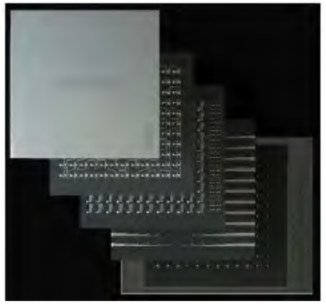


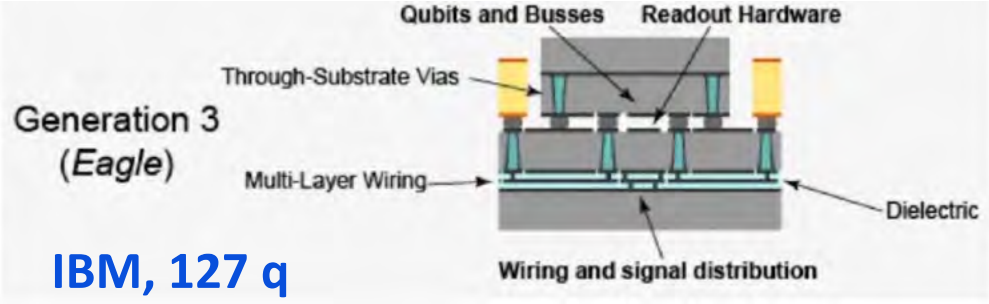




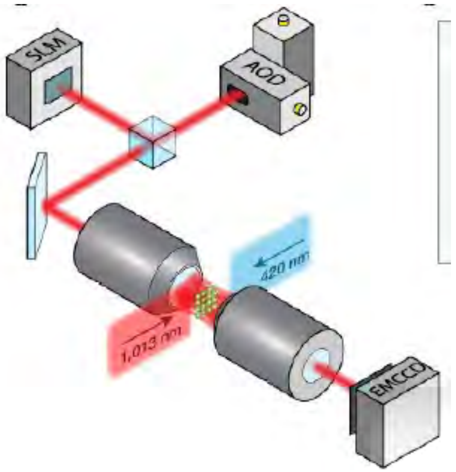
IBM, 65q

Transmon qubits





IBM, 127 q

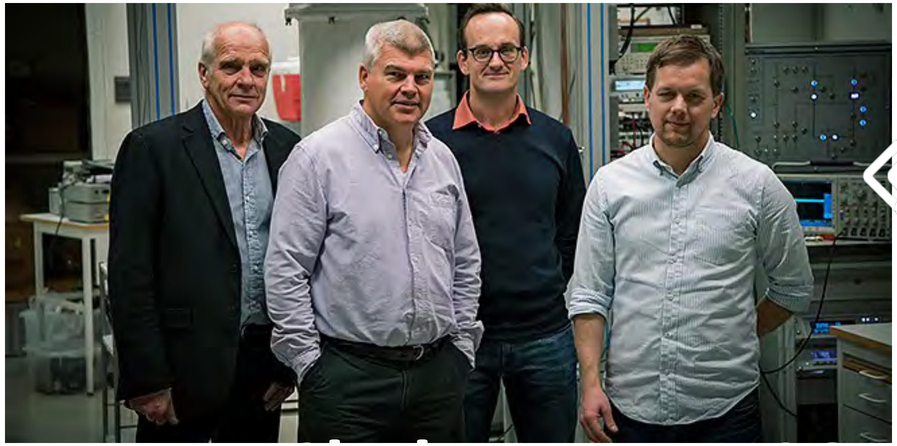


Sweden's quantum technology programme

Wallenberg Centre for Quantum Technologies

WACQT, 2018-2029 MC2, Chalmers U of Tech, Sweden

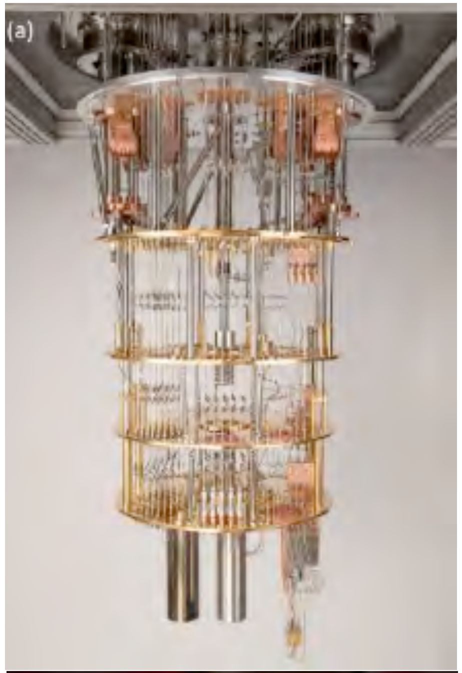
12 years, 150 M€

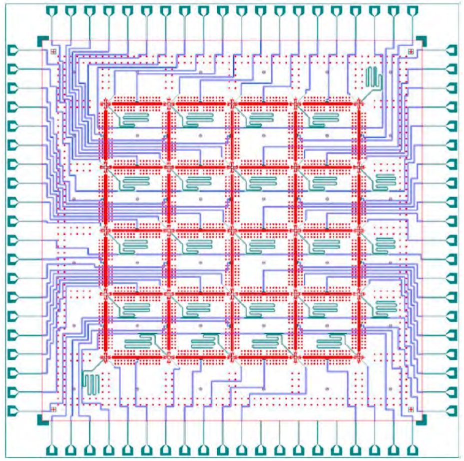


Mission: to build a quantum processor with 100+ superconducting qubits by 2025

https://www.chalmers.se/en/centres/wacqt/Pages/default.aspx

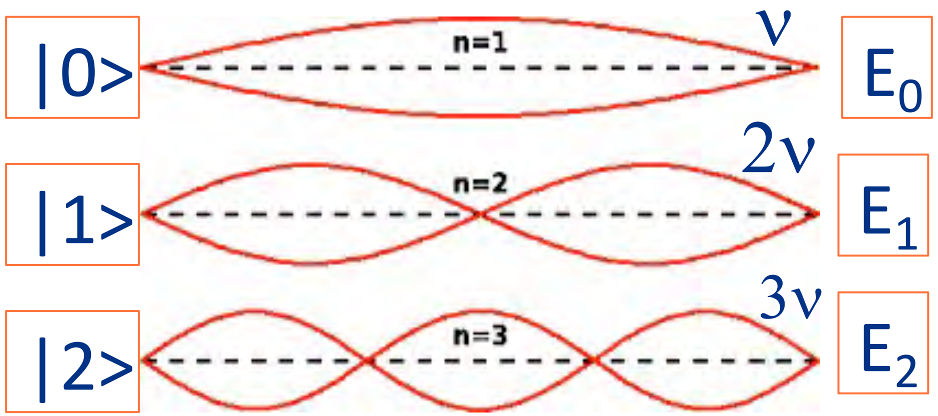
Cryostat
≈ 10 mK



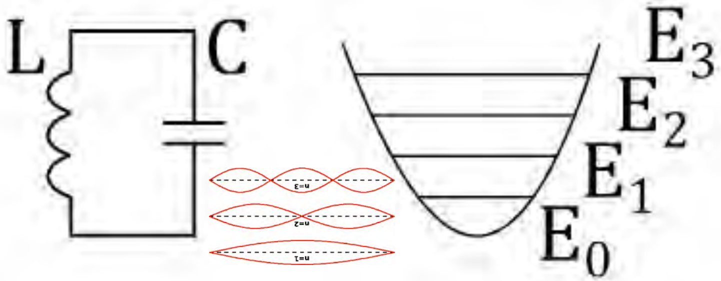


25q Transmon chip under testing

QC/QPU: Superconducting Transmon qubit

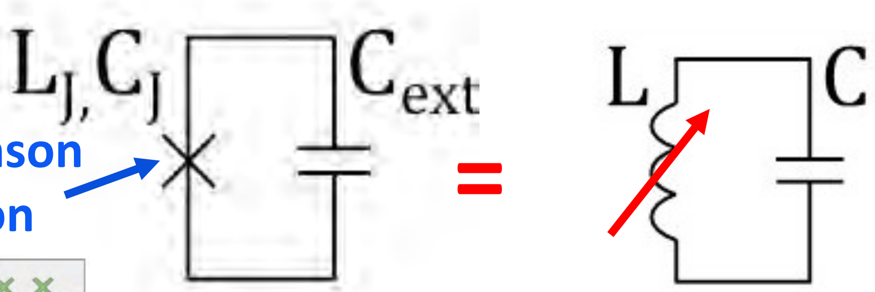


$$\boxed{E = (n+1/2)\ \hbar\omega}$$

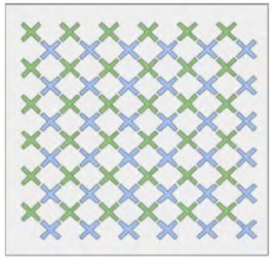


Harmonic oscillator

$$\boxed{|\psi\rangle = a|0\rangle + b|1\rangle + c\ |2\rangle + \ldots.}$$



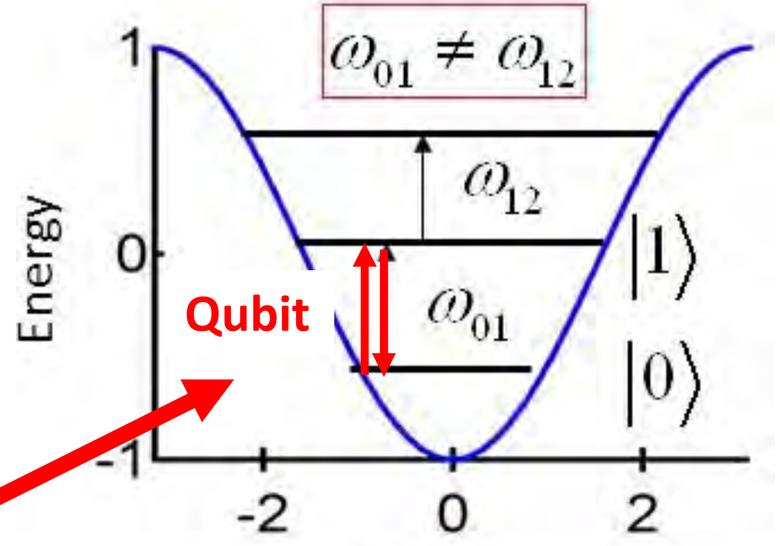
Josephson junction



Qubit

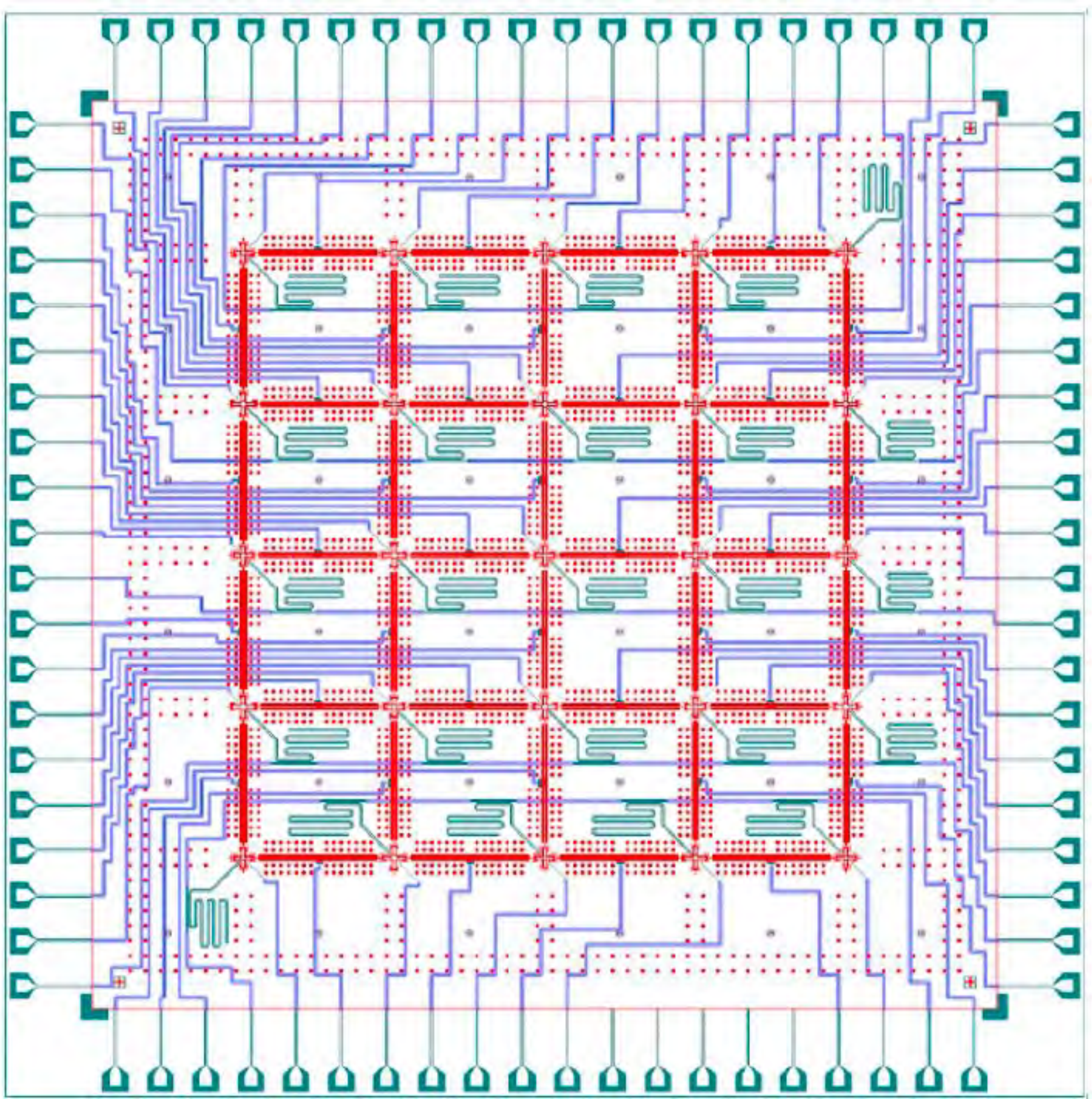
Non-linear quantum resonator

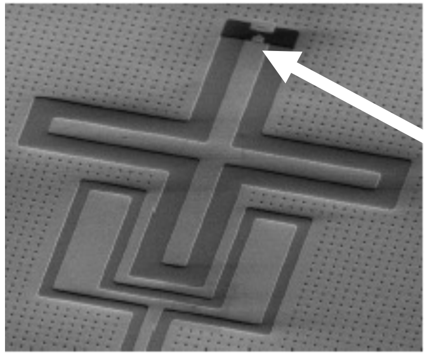
Anharmonic oscillator

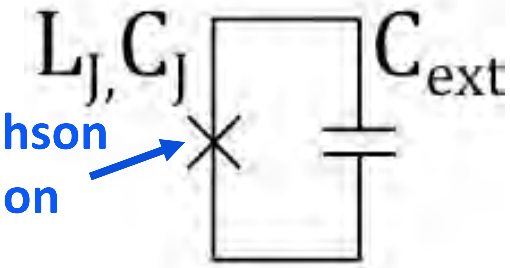


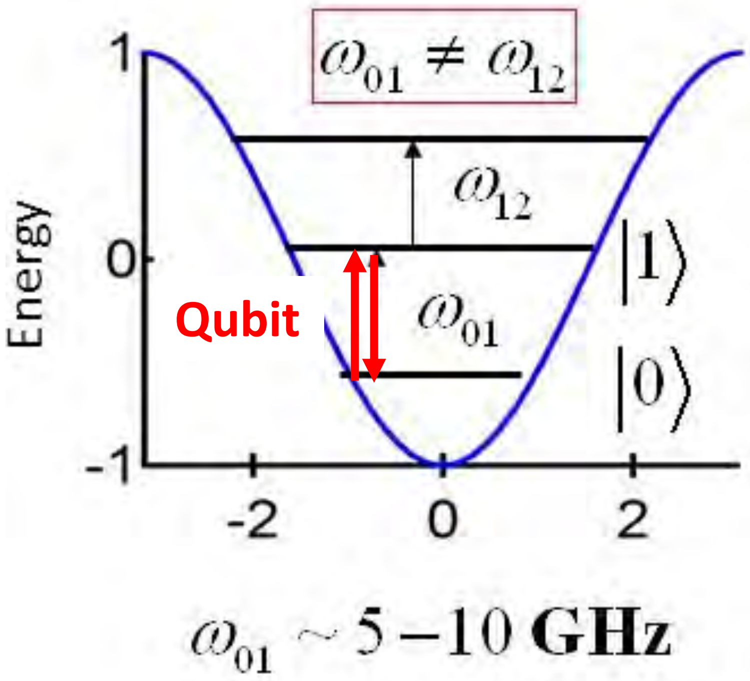
$\omega_{01} \sim 5-10$ GHz

QC/QPU: Superconducting Transmon qubit









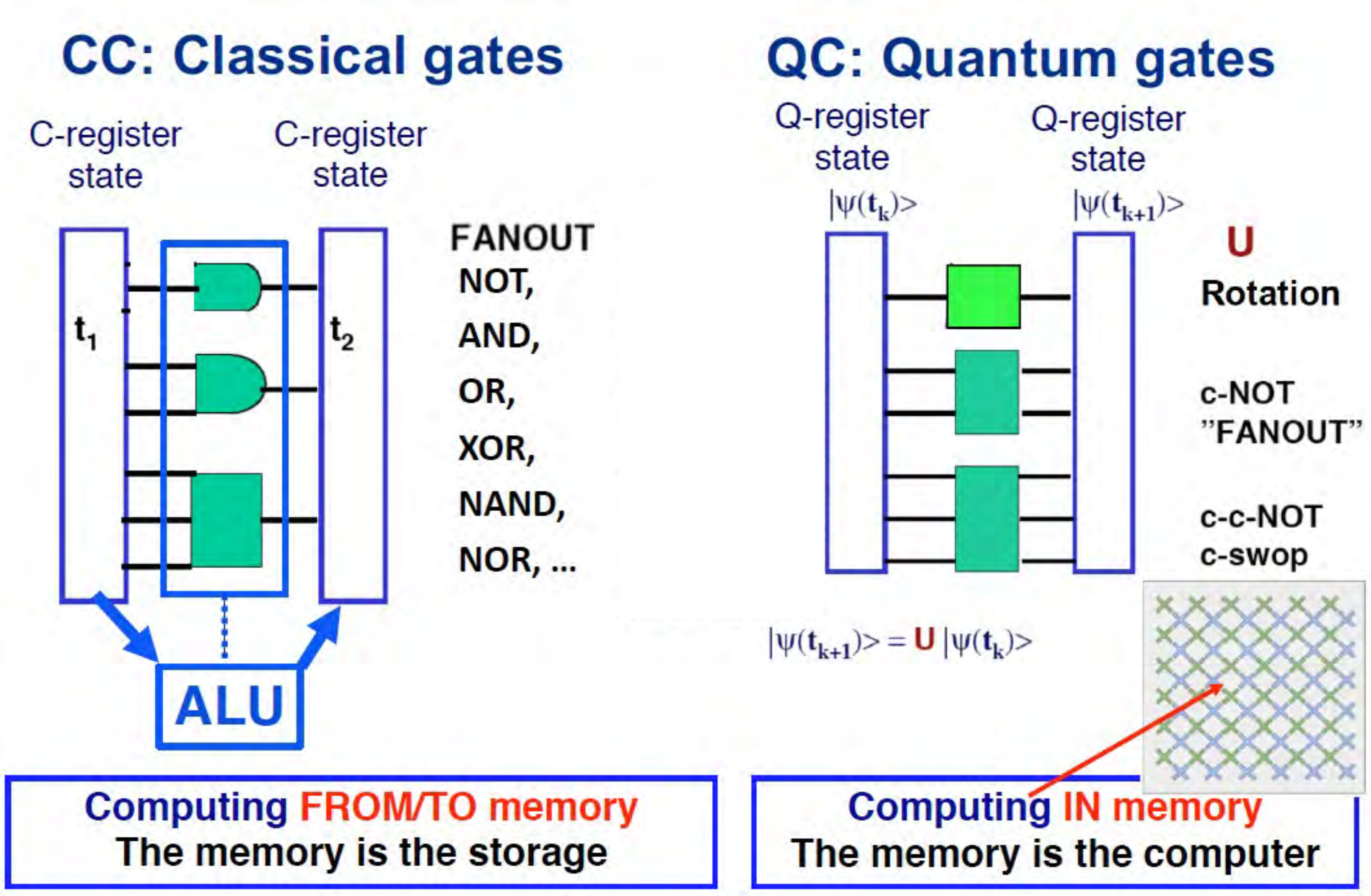
How does QC differ from classical HPC?

Distinct cofigurations

bits

|00..000>
|00..001>
|00..010>
|00..011>
....
|11..110>
|11..111>

Irreversible gates



Superposition
Entanglement

qubits

|00..000> +
|00..001> +
|00..010> +
|00..011> +
.... +
|11..110> +
|11..111>

Reversible gates

- Superconducting, trapped ions, semiconductors
- QC types (digital, analogue, adiabatic, annealing)
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- How the non-QC-expert end-user will benefit

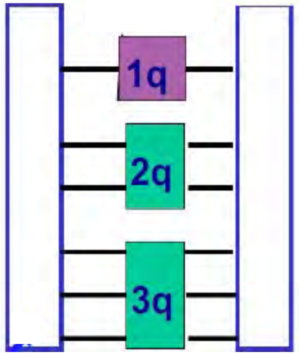
Digital quantum computing (DQC)

Rayleigh-Ritz

$$E(\theta) = \langle \psi(\theta)|\hat{H}|\psi(\theta)\rangle \geq E_0; \quad \hat{H} = \sum_i \hat{H}_i$$

$$|\psi(t)\rangle = U(t,t_0)|\psi(t_0)\rangle$$

$$\boxed{U(t,t_0) = e^{-\frac{i}{\hbar}\hat{H}(t-t_0)}}$$



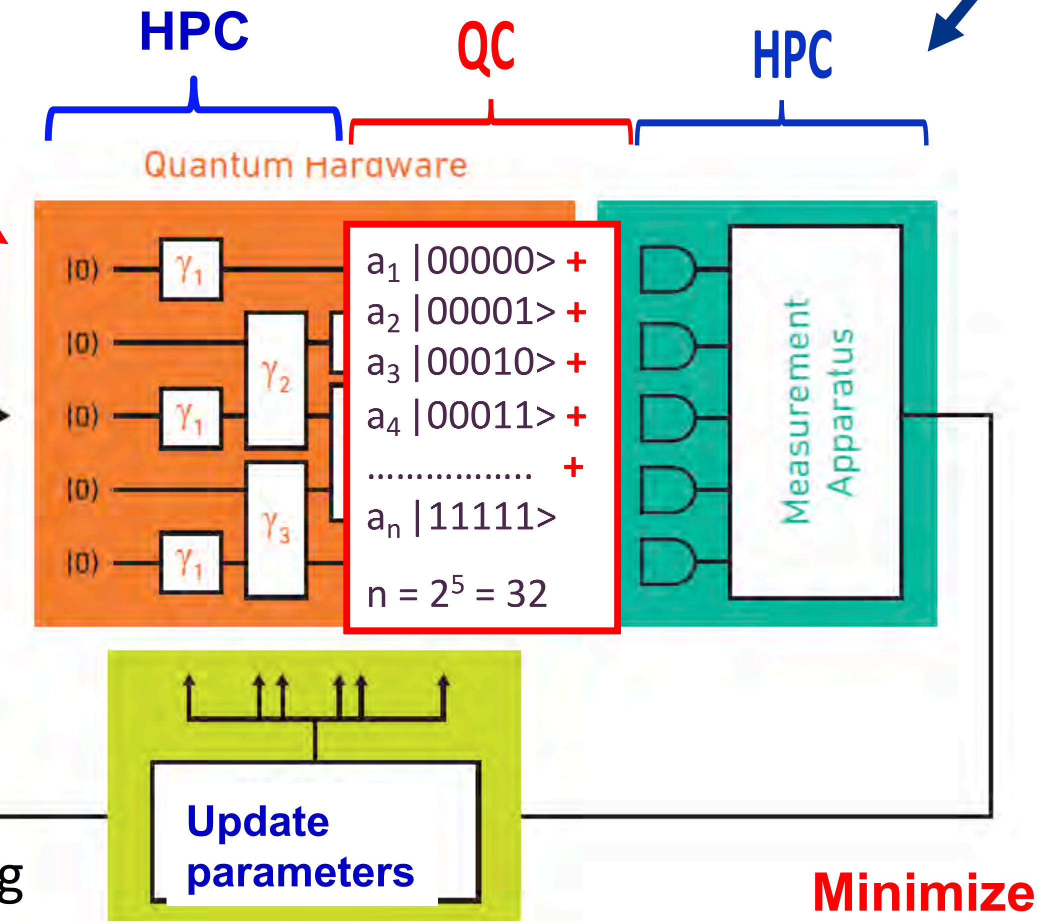
Quantum state tomography

Quantum circuit trial function
(HPC-generated) → $|\psi(\theta)\rangle$

Optimisation

Quantum Approximate Optimization Algorithm (QAOA)

Quantum Variational Eigensolver (VQE)



$$\sigma_1 = \sigma_x = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

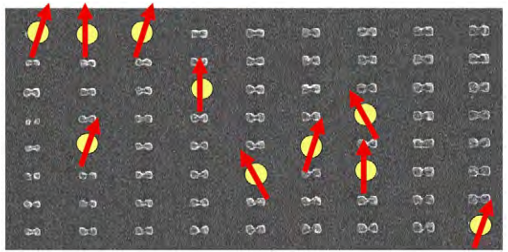
$$\sigma_2 = \sigma_y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}$$

$$\sigma_3 = \sigma_z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

Evaluate cost function

Machine learning

Minimize $\sum_i \langle \psi|\hat{H}_i|\psi\rangle$



Cost function $\hat{H} = \sum_{i\alpha} h_{i\alpha}\, \sigma_{i\alpha} + \sum_{i\alpha,j\beta} h_{i\alpha,j\beta}\, \sigma_{i\alpha}\sigma_{j\beta} + \sum_{i\alpha,j\beta,k\gamma} h_{i\alpha,j\beta,k\gamma}\, \sigma_{i\alpha}\sigma_{j\beta}\sigma_{k\gamma} + \ldots\ldots$

QAOA
Quantum Approximate Optimization Algorithm

Evaluate cost function

Minimize $\sum_i \langle \psi | \hat{H}_i | \psi \rangle$

$$\sigma_1 = \sigma_x = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$
$$\sigma_2 = \sigma_y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}$$
$$\sigma_3 = \sigma_z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

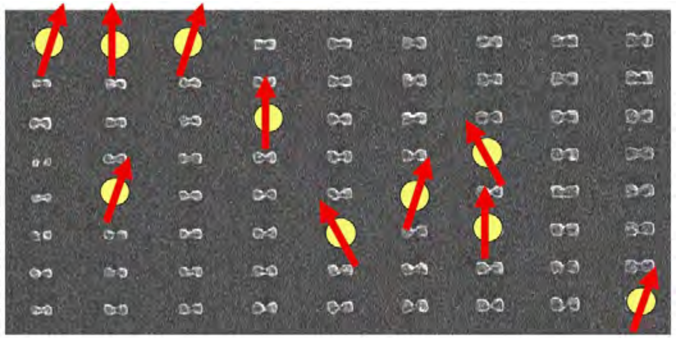
Cost function $\hat{H} = \sum_{i\alpha} h_{i\alpha}\, \sigma_{i\alpha} + \sum_{i\alpha,j\beta} h_{i\alpha,j\beta}\, \sigma_{i\alpha}\sigma_{j\beta} + \sum_{i\alpha,j\beta,k\gamma} h_{i\alpha,j\beta,k\gamma}\, \sigma_{i\alpha}\sigma_{j\beta}\sigma_{k\gamma} + \ldots\ldots$

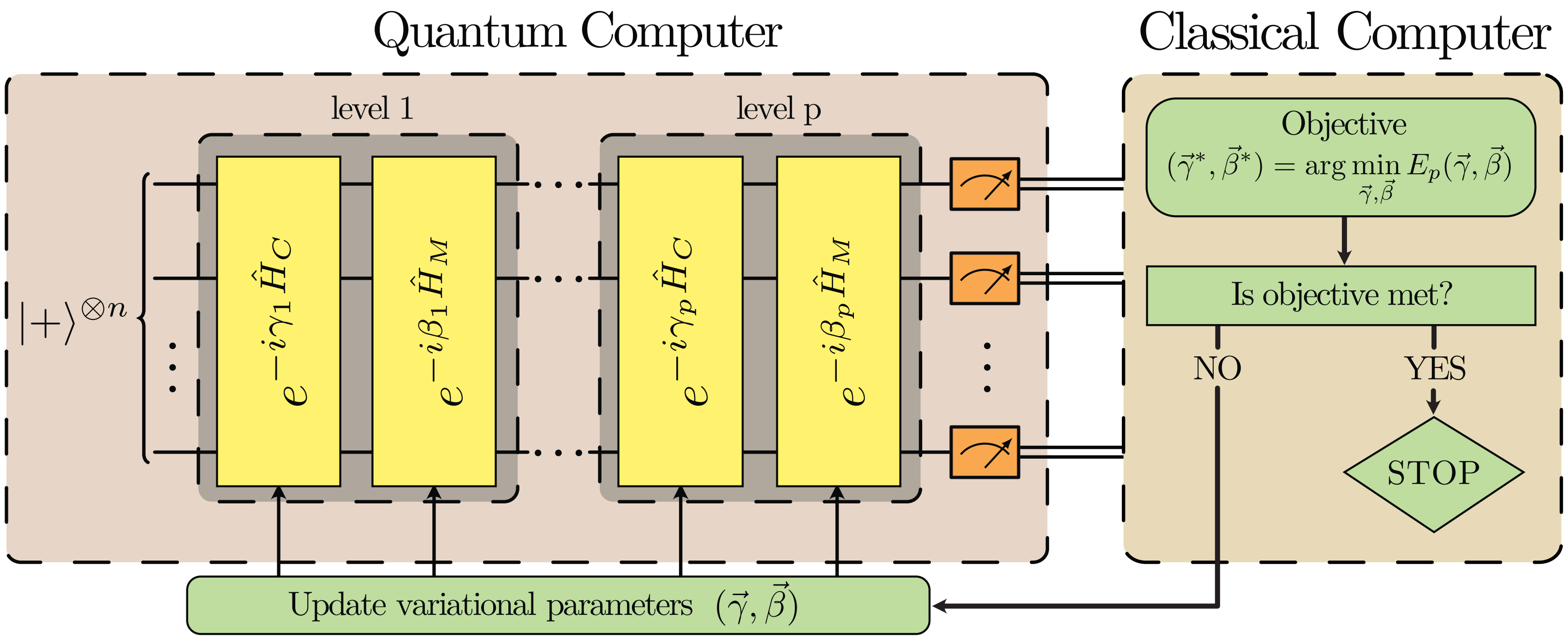
$h_{i\alpha}$

$h_{i\alpha,j\beta}$

$h_{i\alpha,j\beta,k\gamma}$

Tune parameters to to model material systems





Digital-analogue (DAQC) methods

$$\sigma_1 = \sigma_x = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$$

$$\sigma_2 = \sigma_y = \begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}$$

$$\sigma_3 = \sigma_z = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

Evaluate cost function

Minimize $\sum_i \langle \psi | \hat{H}_i | \psi \rangle$

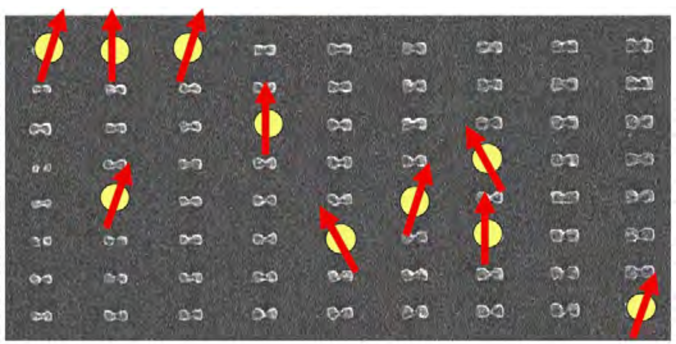
Cost function $$\hat{H} = \sum_{i\alpha} h_{i\alpha}\, \sigma_{i\alpha} + \sum_{i\alpha, j\beta} h_{i\alpha, j\beta}\, \sigma_{i\alpha}\sigma_{j\beta} + \sum_{i\alpha, j\beta, k\gamma} h_{i\alpha, j\beta, k\gamma}\, \sigma_{i\alpha}\sigma_{j\beta}\sigma_{k\gamma} + \ldots\ldots$$

$h_{i\alpha}$

$h_{i\alpha, j\beta}$

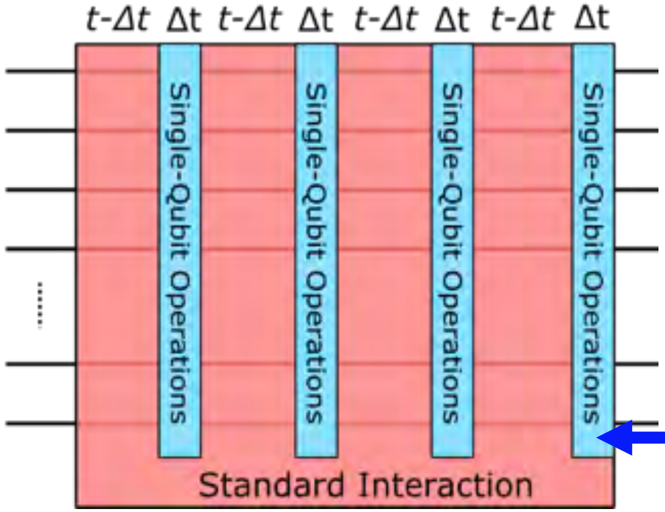
$h_{i\alpha, j\beta, k\gamma}$

Tune parameters to to model material systems



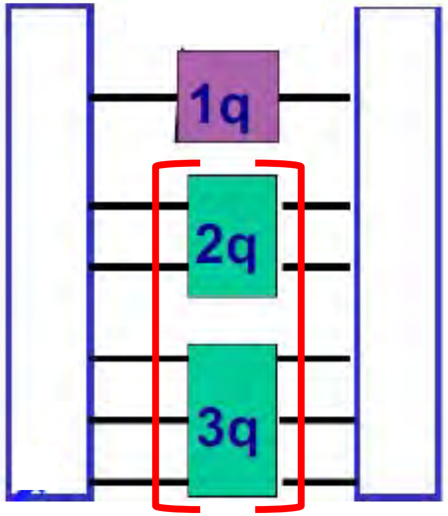
$$|\psi(t)\rangle = U(t, t_0)|\psi(t_0)\rangle$$

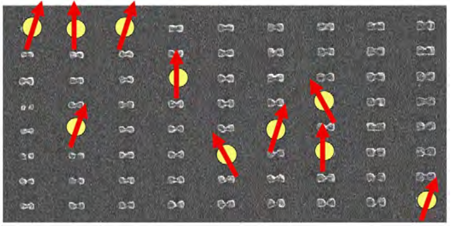
$$\boxed{U(t, t_0) = e^{-\frac{i}{\hbar}\hat{H}(t - t_0)}}$$



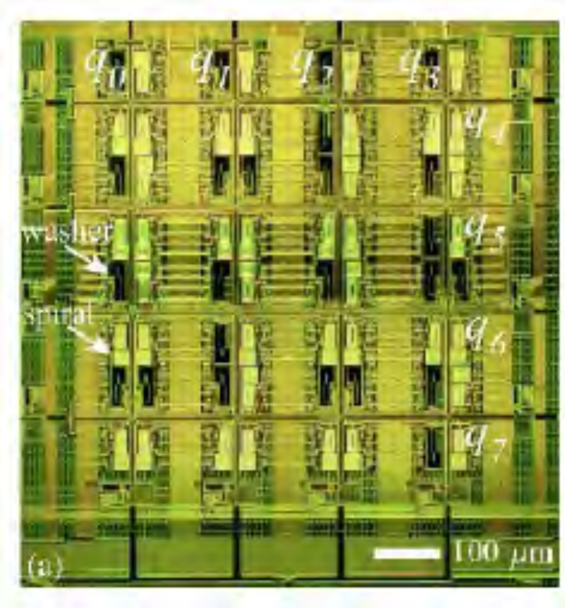
$$\hat{H} = \sum_{i\alpha} h_{i\alpha}\, \sigma_{i\alpha}$$

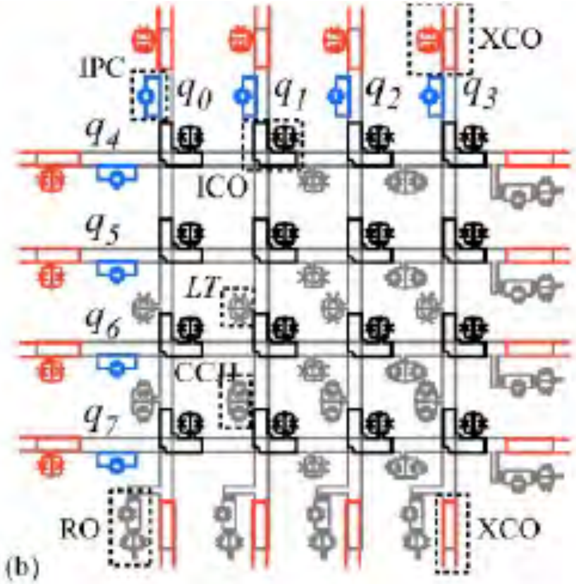
Single quantum operation

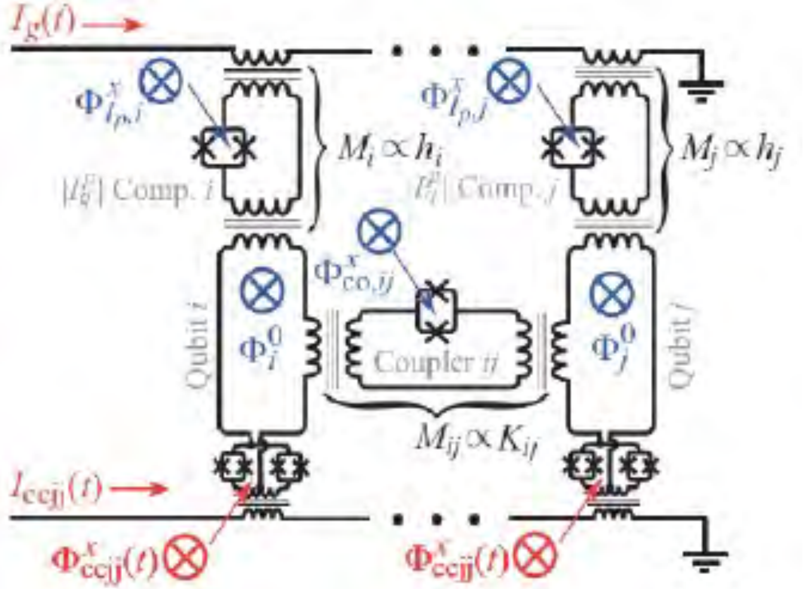




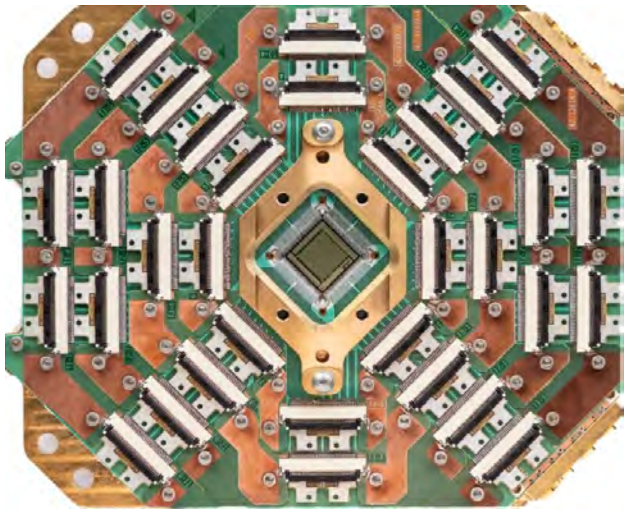
Analogue/adiabatic methods/quantum annealing







The **D-Wave 2Q** processor contains 2000 coupled flux qubits (connectivity 6) at 20 mk using SFQ (classical) circuit technology. The machine is a **Quantum Annealer**. It aims at Adiabatic Quantum Computing, but is not a coherent quantum computer.



The **D-Wave Advantage** processor contains 5000 coupled flux qubits (connectivity 15).

- Superconducting, trapped ions, semiconductors
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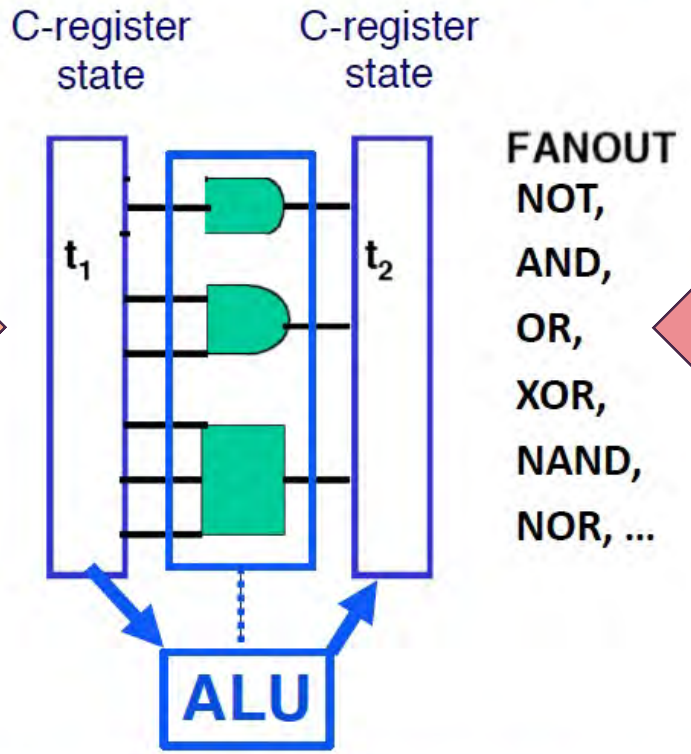
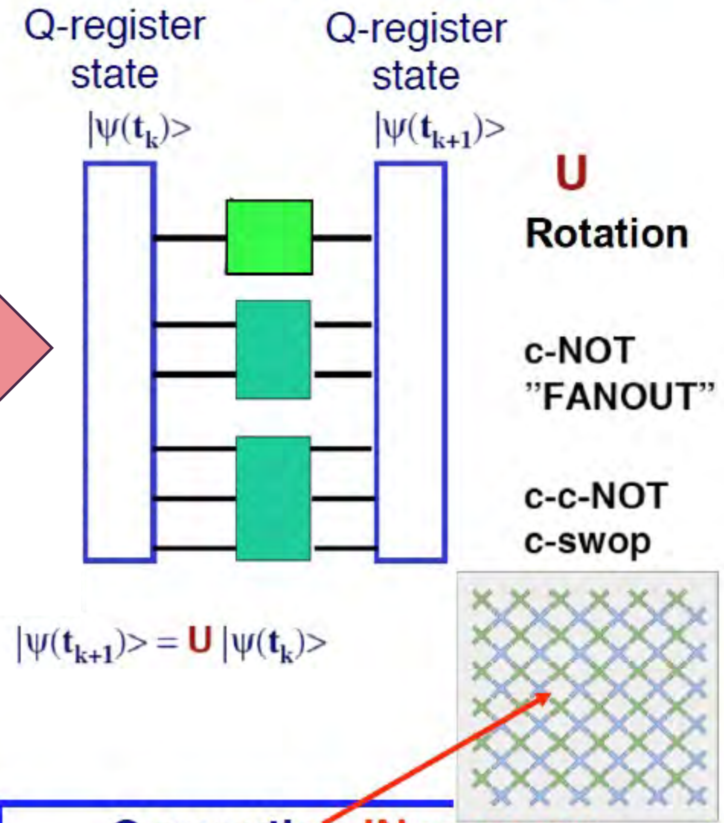
- How the non-QC-expert end-user will benefit

HPC-QC = Classical computer + Q-accelerator

CC: Classical gates



QC: Quantum gates



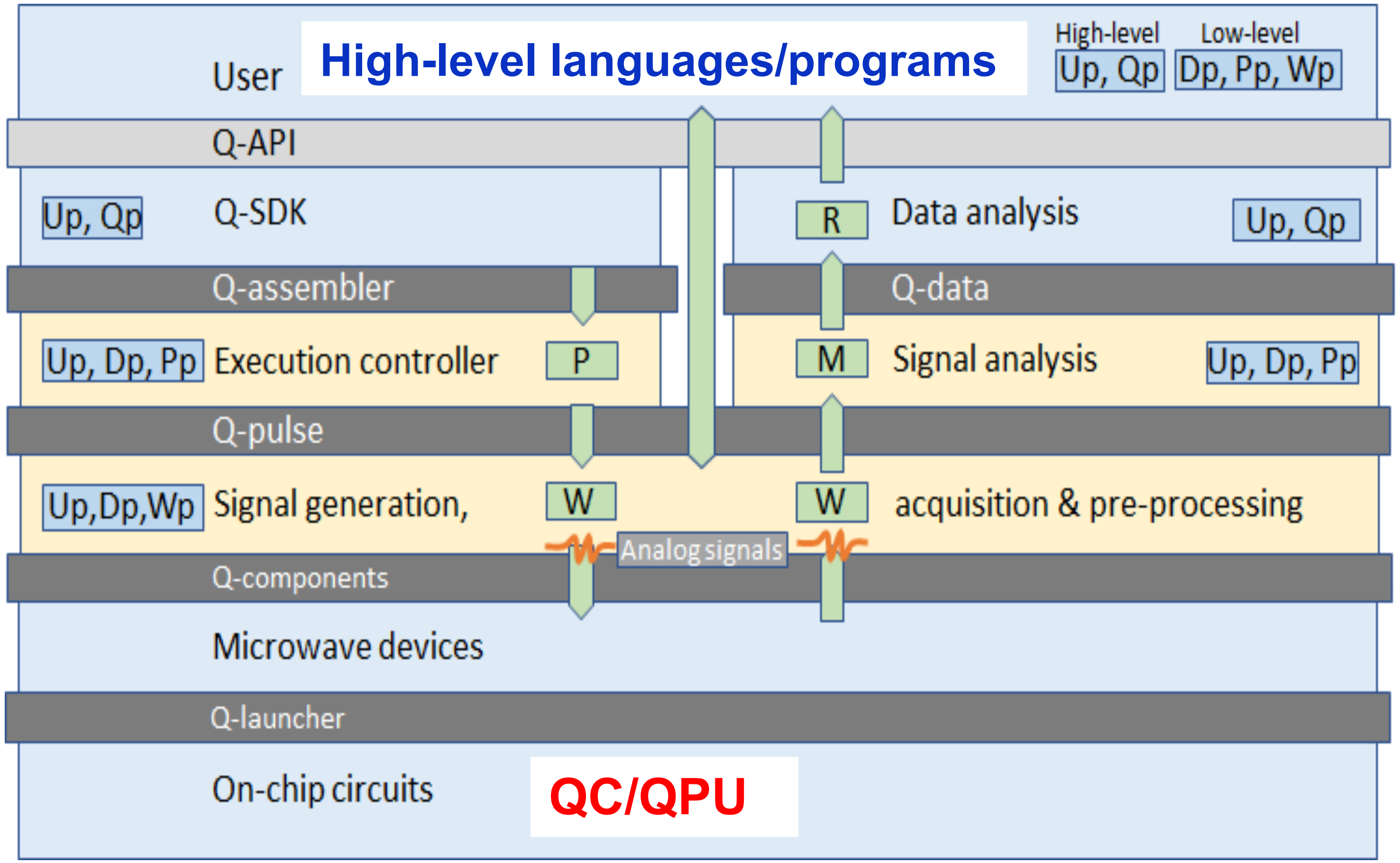
Computing FROM/TO memory
The memory is the storage

Computing IN memory
The memory is the computer

HPC-Q hybrid computer

HPC (mainframe/control) + QC (accelerator/subroutines)

HPC
& cl.
control



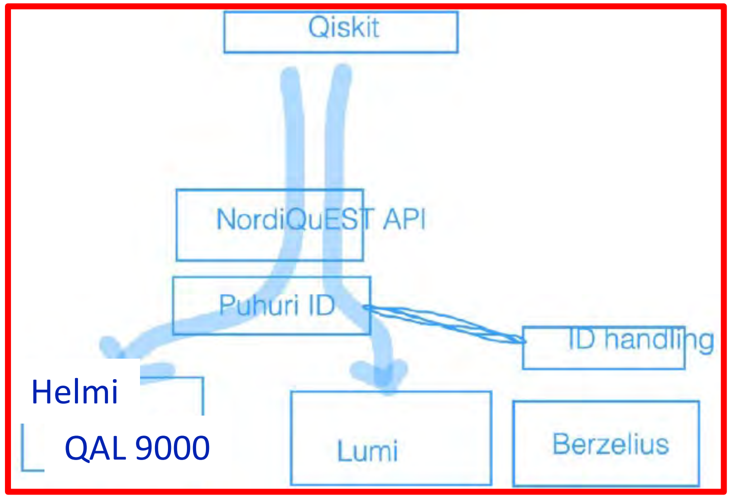
may be
contained in
real-time
system/FPGA

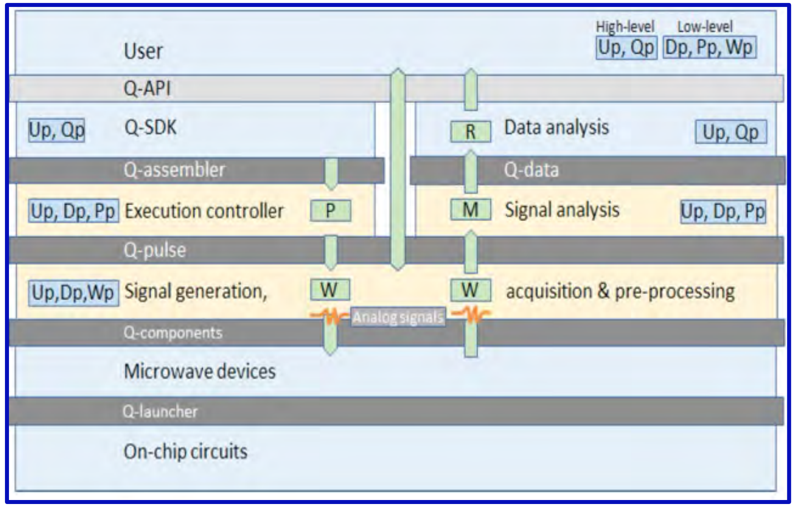
Qiskit (IBM)
Cirq (Google)
Forrest (Rigetti)
Q# (Microsoft)
....

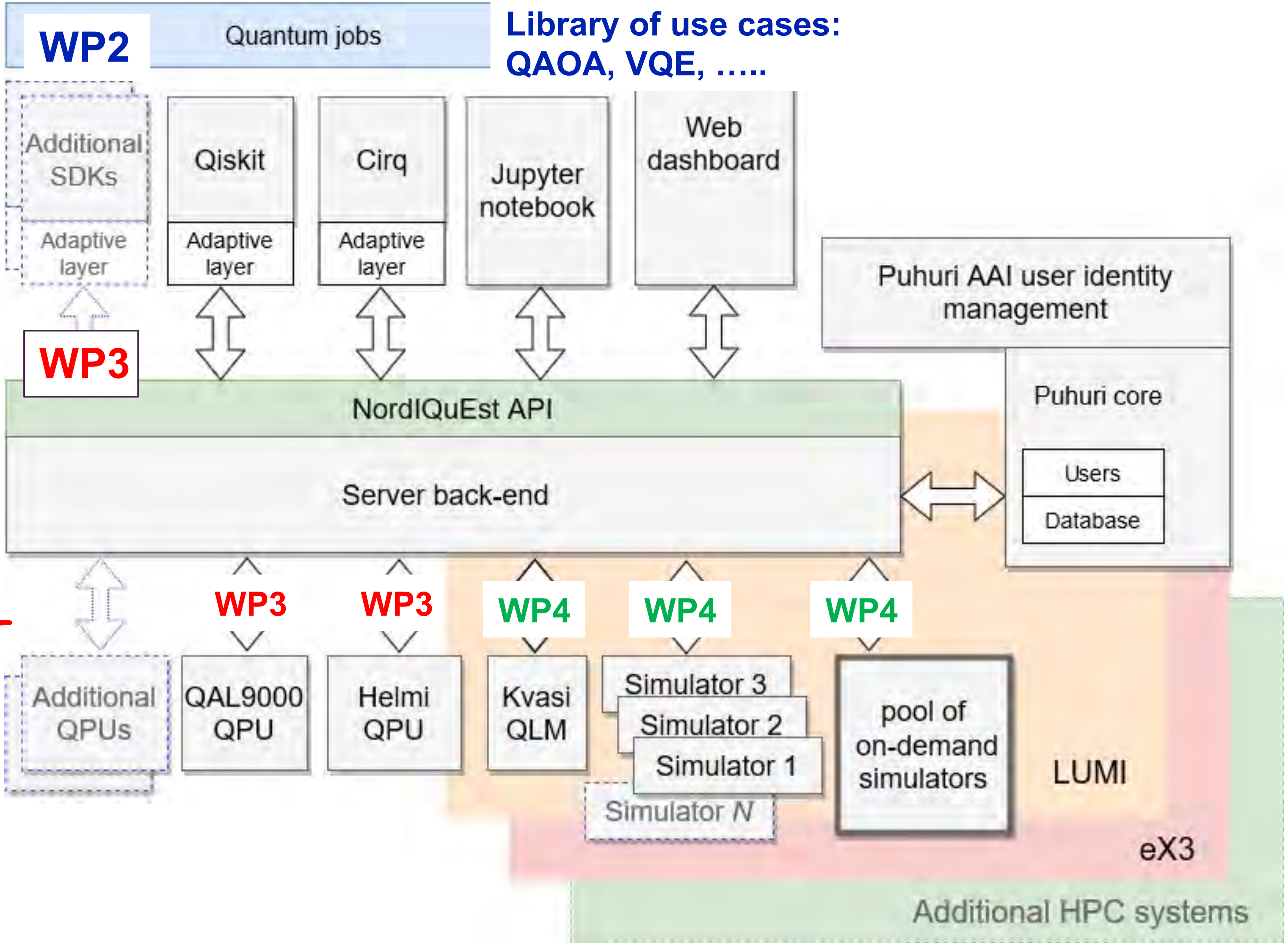
IBM
Google
Rigetti
Alibaba
QuTech
(Delft)
.....

Innsbruck
IonQ
Sandia
Honeywell
....

NordiQuEst in a nutshell







Library of use cases: QAOA, VQE, …..

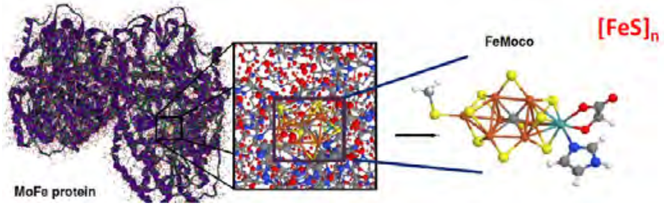
- Superconducting, trapped ions, semiconductors
- QC types (digital, analogue, adiabatic, annealing)
- Hybrid HPC+QC systems
- How the non-QC-expert end-user will benefit

How the non-QC-expert end-user will benefit

K. Michelsen and coworkers, FZ Jülich (2020)

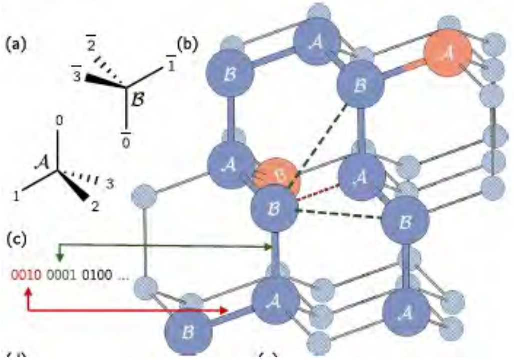
Use cases:

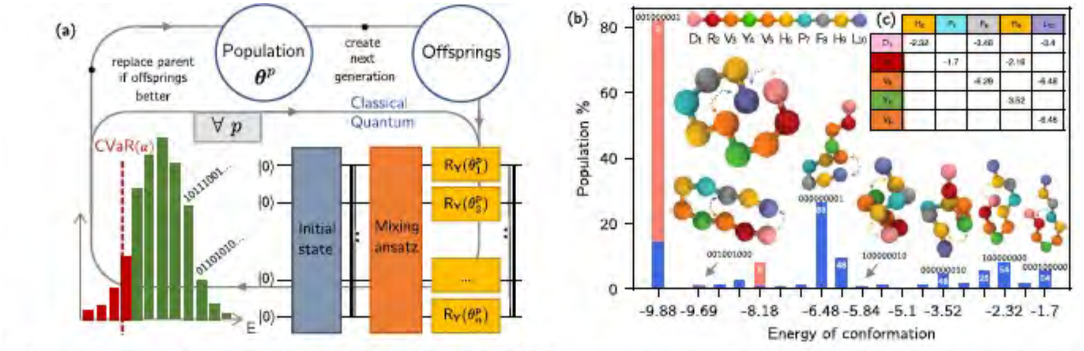
- Optimisation (Logistics, scheduling, ….)



- Chemistry (catalytic molecules, pharma, …)
- Materials science

- Life science





Schematic representation of the folding algorithm and folding process. a Starting from a random population (up-cent

Resource-efficient quantum algorithm for protein folding
Anton Robert, Panagiotis Kl. Barkoutsos, Stefan Woerner and Ivano Tavernelli
npj Quantum Information (2021) 7:38 ; https://doi.org/10.1038/s41534-021-00368-4

HPC-QC roadmaps 2022-2029

- Horizon Europe
- IBM

Development Roadmap

Executed by IBM ✓
On target

IBM **Quantum**

	2019 ✓	2020 ✓	2021 ✓	2022	2023	2024	2025	Beyond 2026
	Run quantum circuits on the IBM cloud	Demonstrate and prototype quantum algorithms and applications	Run quantum programs 100x faster with Qiskit Runtime	Bring dynamic circuits to Qiskit Runtime to unlock more computations	Enhancing applications with elastic computing and parallelization of Qiskit Runtime	Improve accuracy of Qiskit Runtime with scalable error mitigation	Scale quantum applications with circuit knitting toolbox controlling Qiskit Runtime	Increase accuracy and speed of quantum workflows with integration of error correction into Qiskit Runtime

Model Developers

Prototype quantum software applications → Quantum software applications

Machine learning | Natural science | Optimization

Algorithm Developers

Quantum algorithm and application modules ✓

Machine learning | Natural science | Optimization

Quantum Serverless

Intelligent orchestration | Circuit Knitting Toolbox | Circuit libraries

Kernel Developers

Circuits ✓

Qiskit Runtime ✓

Dynamic circuits (on target) | Threaded primitives | Error suppression and mitigation | Error correction

System Modularity

- Falcon ✓ — 27 qubits
- Hummingbird ✓ — 65 qubits
- Eagle ✓ — 127 qubits
- Osprey (on target) — 433 qubits
- Condor — 1,121 qubits
- Flamingo — 1,386+ qubits
- Kookaburra — 4,158+ qubits
- Scaling to 10K-100K qubits with classical and quantum communication
- Heron — 133 qubits x p
- Crossbill — 408 qubits

Globally, much work is dedicated to **comparing HPC simulation of different QAOA implementations**, as well as **comparing QAOA and quantum annealing with classical optimization algorithms** implemented on HPC.

- Guerreschi and Matsuura [2019] found that the QAOA needs several hundred qubits to reach crossover and beat state-of-the-art classical algorithms.
- Lidar and coworkers [Kowalsky 2022] found that the **SATonGPU** algorithm was **superior to D-Wave Advantage (DWA)** solving SAT-problems.
- **FZJ** [Willsch et al. 2021] found that the **DWA quantum annealer** was **superior to HPC simulation of the QAOA** on the maxcut problem describing **flight logistics**
- But **DWA is inferior to the classical SATonGPU** on similar optimisation problems !!

QAOA for Max-Cut requires hundreds of qubits for quantum speed-up
G. G. Guerreschi & A. Y. Matsuura, Scientific Reports 9:6903 (2019)

GPU-accelerated simulations of quantum annealing and the quantum approximate optimization algorithm
D. Willsch, M. Willsch, F. Jin, K. Michielsen, and H. De Raedt; arXiv:2104.03293

Benchmarking Advantage and D-Wave 2000Q quantum annealers with exact cover problems
D. Willsch, M. Willsch, C. D. Gonzalez Calaza, F. Jin, H. De Raedt, M. Svensson, and K. Michielsen; arXiv:2105.02208

3-regular three-XORSAT planted solutions benchmark of classical and quantum heuristic optimizers
Matthew Kowalsky, Tameem Albash, Itay Hen and Daniel A Lidar, Quantum Sci. Technol. 7 (2022) 025008

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Solver	Parallel tempering	Fujitsu digital annealer unit
Hardware	Single CPU	ASIC
Connectivity	Full, dense	Full, dense
Max QUBO size n	RAM-limited, 10 000	8192/4096/2048, *precision dependent
Precision	64 bit float $\approx 10^{-16}$	16/32/64 bit (signed int) $\approx 10^{-4}/10^{-9}/10^{-19}$
Parallelization	1 per CPU core	8 per DA
Accessed via	USC-UNM code	DA Center Japan 4/25/2020

Toshiba simulated bifurcation machine	D-Wave advantage 1.1	SATonGPU
Single GPU	Superconducting qubits	Single GPU
small n: full, dense; large n: full, sparse	Pegasus (Deg. 15)	Full, dense
10 000 max, $10^6 J_{ij} \neq 0$	Clique: 128, 3R3X: $\approx$ 256, native: 5436	RAM-limited, >10 000
64 bit float $\approx 10^{-16}$	Noise-limited. $\approx$5 bit or 10^{-2}	64 bit float $\approx 10^{-16}$
40 per GPU	$\lfloor n_{\max}/n \rfloor$ replicas *connectivity dependent	327680 replicas
Amazon Web Services [51] 8/20/2020	LEAP cloud 10/31/2020	n/a

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