

# Measuring Performance of Fault Tolerant Quantum Computation

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# Achieving reliable quantum computing

## Recently, Microsoft & Quantinuum:

arXiv:2404.02280: "Demonstration of logical qubits and repeated error correction with better-than-physical error rates", April 2024

On Quantinuum's H2 machine, entangled logical qubits exhibit a circuit error rate of  $10^{-5}$  versus a physical circuit error rate of  $8 \times 10^{-3}$ .

For the first time, successfully demonstrated multiple rounds of active syndrome extractions, a critical component of reliable quantum computing

Required  $\sim 350$  physical two-qubit operations and over 75 physical timesteps



# Quantum Computing Implementation Levels



## Level 1 | Foundational

Physical qubits

Quantum advantage:

~60 physical qubits, contrived problems



## Level 2 | Resilient

Logical qubits

Scientific advantage:

100 logical qubits,  $10^{-8}$  error rate



## Level 3 | Scale

Quantum supercomputer

Commercial advantage:

1000 logical qubits,  $10^{-12}$  error rate

## Reliable Quantum Operations Per Second (rQOPS)

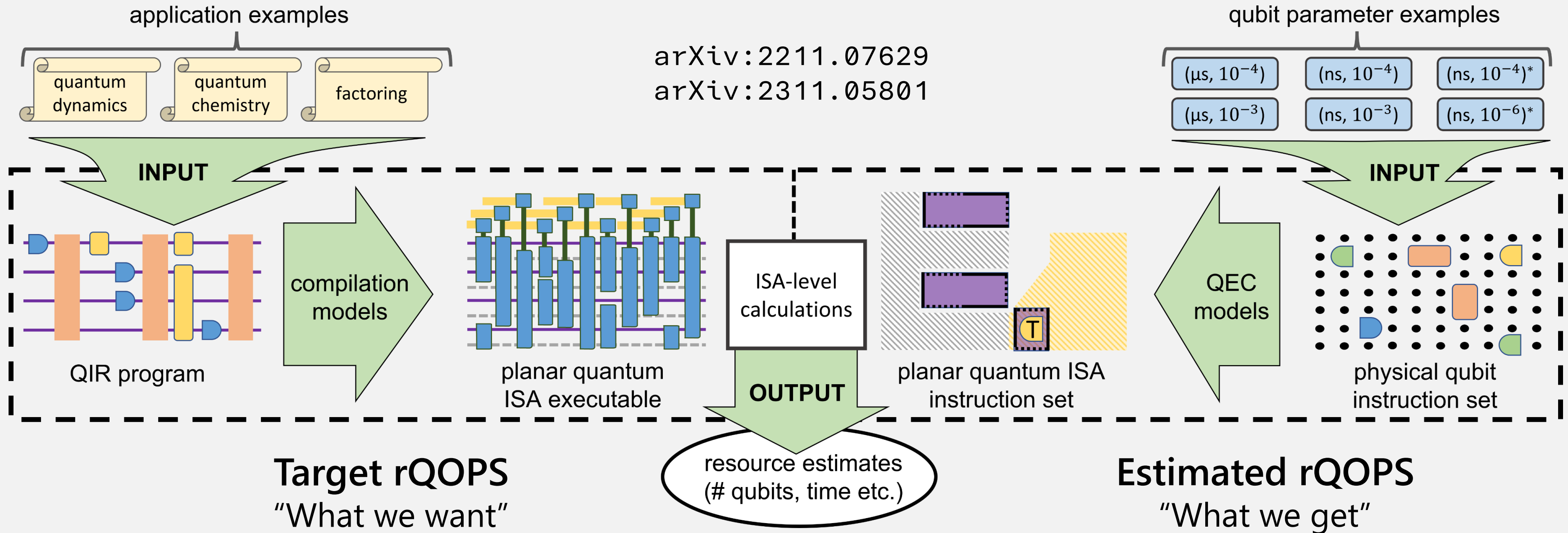
$$R = Q \times f, \text{ at } \varepsilon_L \text{ error rate}$$

$Q$ : number of reliable logical qubits

$f$ : logical clock speed (in hertz)

$\varepsilon_L$ : logical error rate

# Azure Quantum Resource Estimator



Based on:

- Size of logical circuit we want to execute
- Target error of outcome
- Target run-time

Based on:

- Hardware and systems architecture parameters
- QEC scheme + distance used

# Four Sample Applications

- Ising model
- Hubbard model
- Heisenberg model
- Quantum chemistry

# Ising Model Dynamics

- <https://aka.ms/AQRE/2DIsing>
- Logical resource estimates for  $N \times N$  Ising model

	10 × 10	20 × 20	30 × 30
qubits	230	858	1886
depth	$9.0 \times 10^4$	$5.8 \times 10^5$	$1.9 \times 10^6$
error	$1.6 \times 10^{-10}$	$6.7 \times 10^{-12}$	$9.5 \times 10^{-13}$
target rQOPS	119	2881	20399

- Target run-time: 2 days

The screenshot shows a GitHub repository for 'qsharp' with a notebook titled 'Resource estimation for simulating a 2D Ising Model Hamiltonian'. The notebook content includes:

**Resource estimation for simulating a 2D Ising Model Hamiltonian**

In this Python+Q# notebook we demonstrate how to estimate the resources for quantum dynamics, specifically the simulation of an Ising model Hamiltonian on an  $N \times N$  2D lattice using a *fourth-order Trotter Suzuki product formula* assuming a 2D qubit architecture with nearest-neighbor connectivity.

First, we load the necessary Python packages.

```
In [ ]: import qsharp
import pandas as pd
```

**Background: 2D Ising model**

The Ising model is a mathematical model of ferromagnetism in a lattice (in our case a 2D square lattice) with two kinds of terms in the Hamiltonian: (i) an interaction term between adjacent sites and (ii) an external magnetic field acting at each site. For our purposes, we consider a simplified version of the model where the interaction terms have the same strength and the external field strength is the same at each site. Formally, the Ising model Hamiltonian on an  $N \times N$  lattice we consider is formulated as:

$$H = -J \underbrace{\sum_{i,j} Z_i Z_j}_B + g \underbrace{\sum_j X_j}_A$$

where  $J$  is the interaction strength,  $g$  is external field strength.

The time evolution  $e^{-iHt}$  for the Hamiltonian is simulated with the fourth-order product formula so that any errors in simulation are sufficiently small. Essentially, this is done by simulating the evolution for small slices of time  $\Delta$  and repeating this for  $nSteps = t/\Delta$  to obtain the full time evolution. The Trotter-Suzuki formula for higher orders can be recursively defined using a *fractal decomposition* as discussed in Section 3 of [Hatanao and Suzuki's survey](#). Then the fourth order formula  $U_4(\Delta)$  can be constructed using the second-order one  $U_2(\Delta)$  as follows.

$$U_2(\Delta) = e^{-iA\Delta/2} e^{-iB\Delta} e^{-iA\Delta/2}$$

# Heisenberg Model

- <https://aka.ms/AQRE/2DHeisenberg>

- Logical resource estimates for  $N \times N$  Heisenberg model

	20 × 20	30 × 30	40 × 40
qubits	858	1886	3315
depth	$6.9 \times 10^8$	$1.5 \times 10^9$	$2.6 \times 10^9$
error	$5.5 \times 10^{-15}$	$1.2 \times 10^{-15}$	$3.8 \times 10^{-16}$
target rQOPS	$1.0 \times 10^6$	$4.7 \times 10^6$	$1.4 \times 10^7$

- Target run-time: 1 week

Resource Estimation for simulating a 2D Heisenberg Model Hamiltonian

In this Python + Q# notebook we demonstrate how to *efficiently* estimate the resources for simulating a Heisenberg model Hamiltonian on an  $N \times N$  2D lattice using a *fourth-order Trotter Suzuki product formula* assuming a 2D planar qubit architecture with nearest-neighbor connectivity.

First, we load the necessary packages.

```
In [ ]: import qsharp
import pandas as pd
```

### Background: 2D Heisenberg Model

The quantum Heisenberg model is a statistical mechanical model used in the study of magnetic systems. The family of Heisenberg model Hamiltonians considered in this notebook consist of three types of interaction terms between adjacent lattice sites:  $\{X \otimes X, Y \otimes Y, Z \otimes Z\}$ . For our purposes we consider that the interaction strength  $J$  is the same for each term. Formally, the Heisenberg model Hamiltonian on an  $N \times N$  lattices divided into sets of commuting terms is formulated as:

$$H = J \underbrace{\sum_{i,j} X_i \otimes X_j}_A + J \underbrace{\sum_{i,j} Z_i \otimes Z_j}_B + J \underbrace{\sum_{i,j} Y_i \otimes Y_j}_C.$$

The time evolution  $e^{-iHt}$  for the Hamiltonian is simulated with the fourth-order Trotter-Suzuki product formula so that any errors in simulation are sufficiently small. Essentially, this is done by simulating the evolution for small slices of time  $\Delta$  and repeating this for  $nSteps = \lceil t/\Delta \rceil$  to obtain the full time evolution. The Trotter-Suzuki formula for higher orders can be recursively defined using a *fractal decomposition* as discussed in Section 3 of [Hatanao and Suzuki's survey](#). Then the fourth order formula  $U_4(\Delta)$  can be constructed using the second-order one  $U_2(\Delta)$  as follows.



# Hubbard Model

- <https://aka.ms/AQRE/2DHubbard>
- Logical resource estimates for  $N \times N$  Hubbard model

	20 × 20	30 × 30	40 × 40
qubits	3315	7371	13028
depth	$1.2 \times 10^9$	$2.5 \times 10^9$	$4.5 \times 10^9$
error	$8.5 \times 10^{-16}$	$1.8 \times 10^{-16}$	$5.6 \times 10^{-17}$
target rQOPS	$6.5 \times 10^6$	$3.2 \times 10^7$	$9.8 \times 10^7$

- Target run-time: 1 week

The screenshot shows a GitHub repository for 'qsharp' with a notebook file named 'estimation-hubbard-2D.ipynb'. The notebook content includes:

### Resource estimation for simulating a 2D Hubbard model

In this Python + Q# notebook we demonstrate how to *efficiently* estimate the resources required to simulate a Hubbard model Hamiltonian on an  $N \times N$  2D lattice using a *fourth-order Trotter Suzuki product formula* assuming a 2D planar qubit architecture with nearest-neighbor connectivity.

First, load the necessary packages.

```
In [ ]: import qsharp
import pandas as pd
```

### Background: 2D Hubbard Model

The Hubbard Model is a simple model of interacting particles in a lattice (in our case a 2D square lattice) with two kinds of terms in the Hamiltonian: (i) a hopping term between adjacent sites and (ii) a potential term for onsite interactions. Formally, a Hubbard model Hamiltonian on an  $N \times N$  lattice where each site has two spins {up, dn} is given as:

$$H = U \underbrace{\sum_{i,j} c_{(i,j),\text{up}}^\dagger c_{(i,j),\text{up}} c_{(i,j),\text{dn}}^\dagger c_{(i,j),\text{dn}}}_B - t \underbrace{\sum_{\sigma \in \{\text{up}, \text{dn}\}, i, j} (c_{(i,j),\sigma}^\dagger c_{(i+1,j),\sigma} + c_{(i+1,j),\sigma}^\dagger c_{(i,j),\sigma})}_A - t \underbrace{\sum_{\sigma \in \{\text{up}, \text{dn}\}, i, j} (c_{(i,j),\sigma}^\dagger c_{(i,j+1),\sigma} + c_{(i,j+1),\sigma}^\dagger c_{(i,j),\sigma})}_C$$

where  $c$  is the annihilation operator,  $c^\dagger$  is the creation operator, the first set of terms are the on-site repulsion terms, the second set are the vertical row hops and last set is the horizontal column hops.

### Converting to Pauli terms

The first step needed to simulate  $H$  is to map the fermionic terms into *local* Pauli operations involving only a few qubits. When the Hamiltonian acts on a 1D lattice, using the Jordan-Wigner would suffice. However, for the 2D lattice, either row or column hops will end up being non-local terms involving  $O(N)$  qubits. To overcome this, we use the [Verstraete-Cirac](#) encoding to convert the repulsion and hopping terms into local Pauli operators involving at most 4 qubits at a time. This is done by adding

# Quantum Chemistry

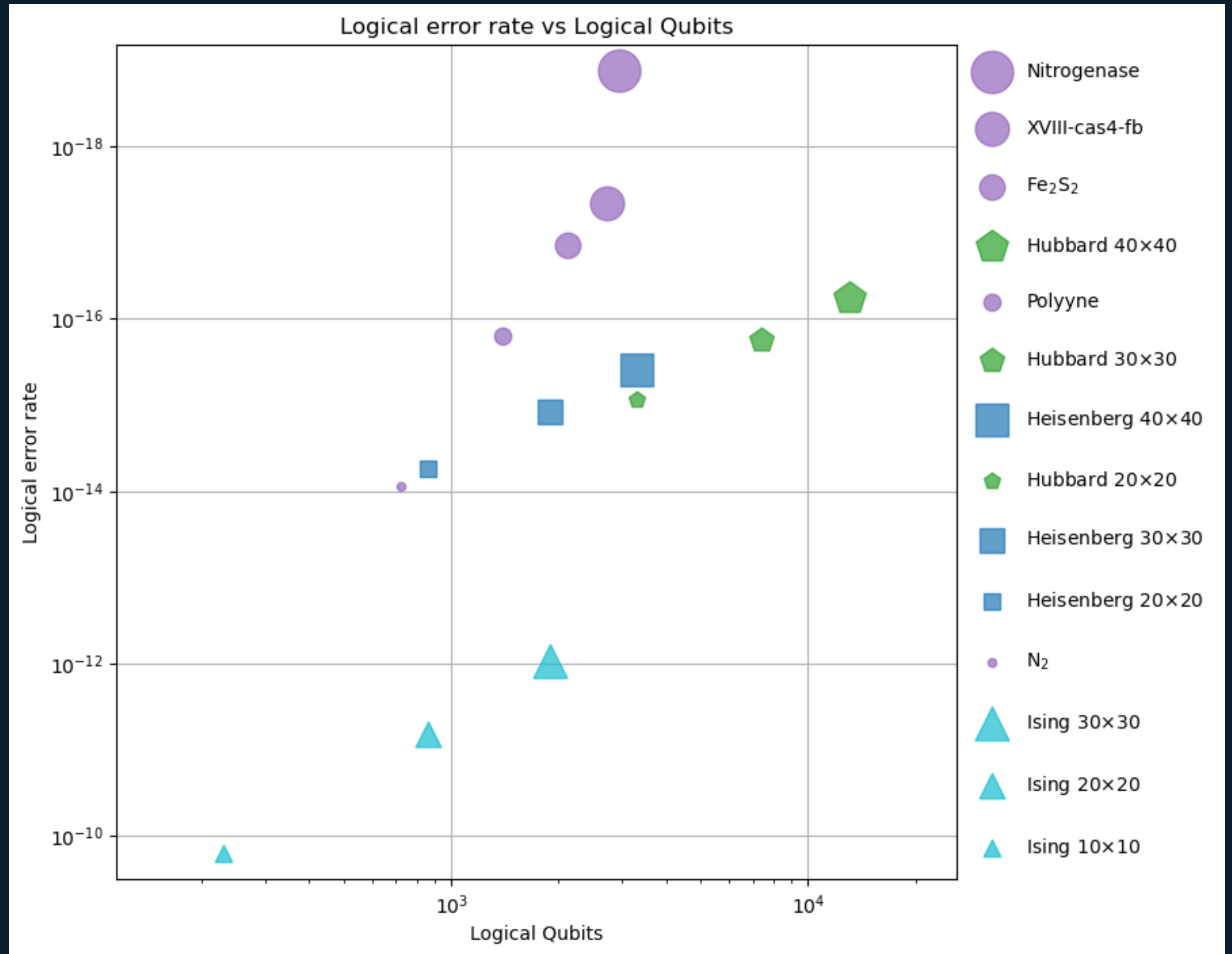
- <https://aka.ms/AQRE/DoubleFactorizedChemistry>
- Logical resource estimates for various molecules:

	$N_2$	Polyyne	$Fe_2S_2$	XVIII-cas4-fb	Nitrogenase
qubits	721	1394	2109	2740	2956
depth	$5.7 \times 10^8$	$1.6 \times 10^{10}$	$1.2 \times 10^{11}$	$2.7 \times 10^{11}$	$8.6 \times 10^{12}$
error	$8.6 \times 10^{-15}$	$1.6 \times 10^{-16}$	$1.4 \times 10^{-17}$	$4.6 \times 10^{-18}$	$1.3 \times 10^{-19}$
target rQOPS	$3.2 \times 10^5$	$1.7 \times 10^7$	$2.0 \times 10^8$	$6.0 \times 10^8$	$2.1 \times 10^{10}$

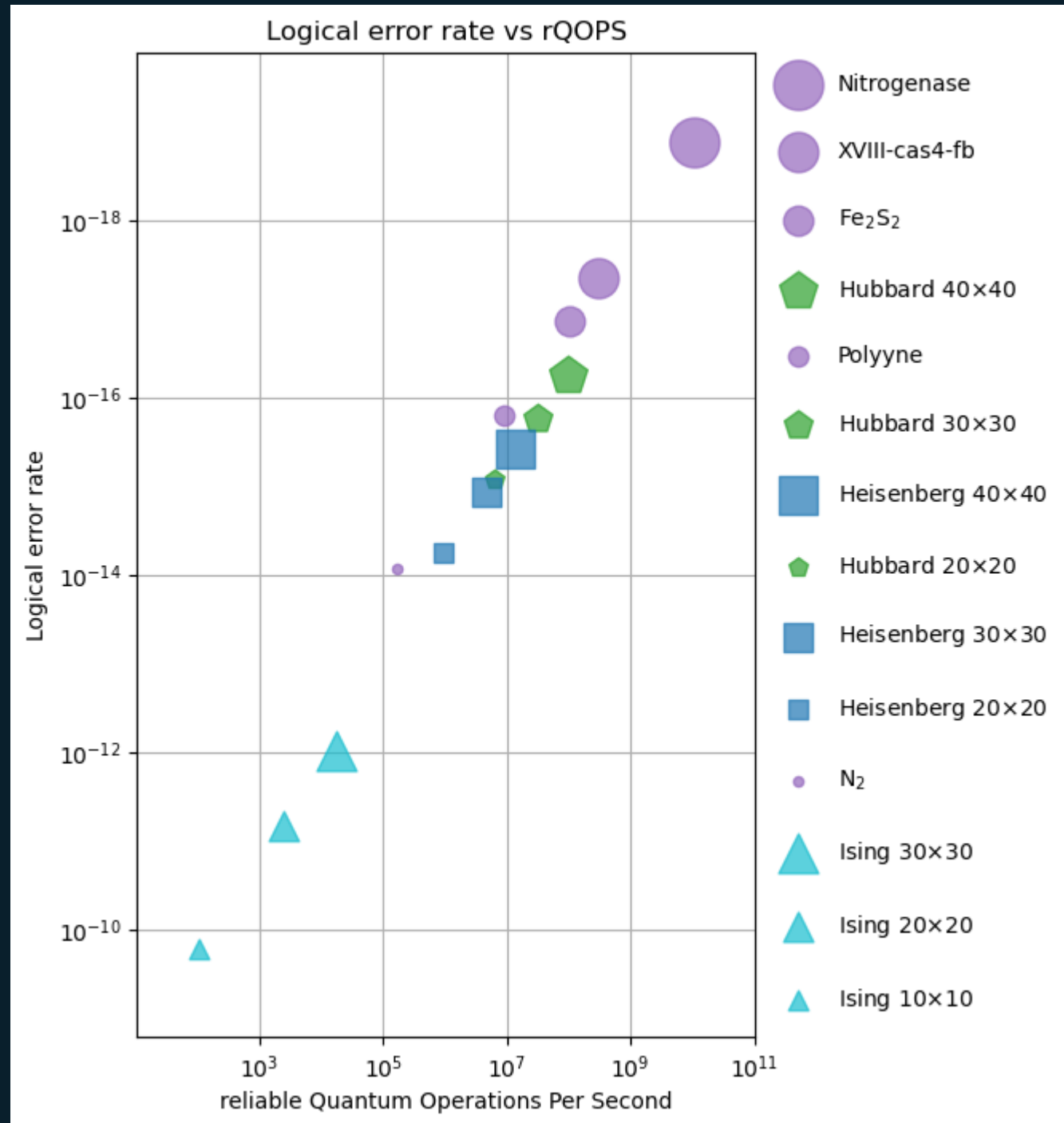
- Target run-time: 28 days

# Logical Qubits vs Logical Errors

Ratio depends on algorithm

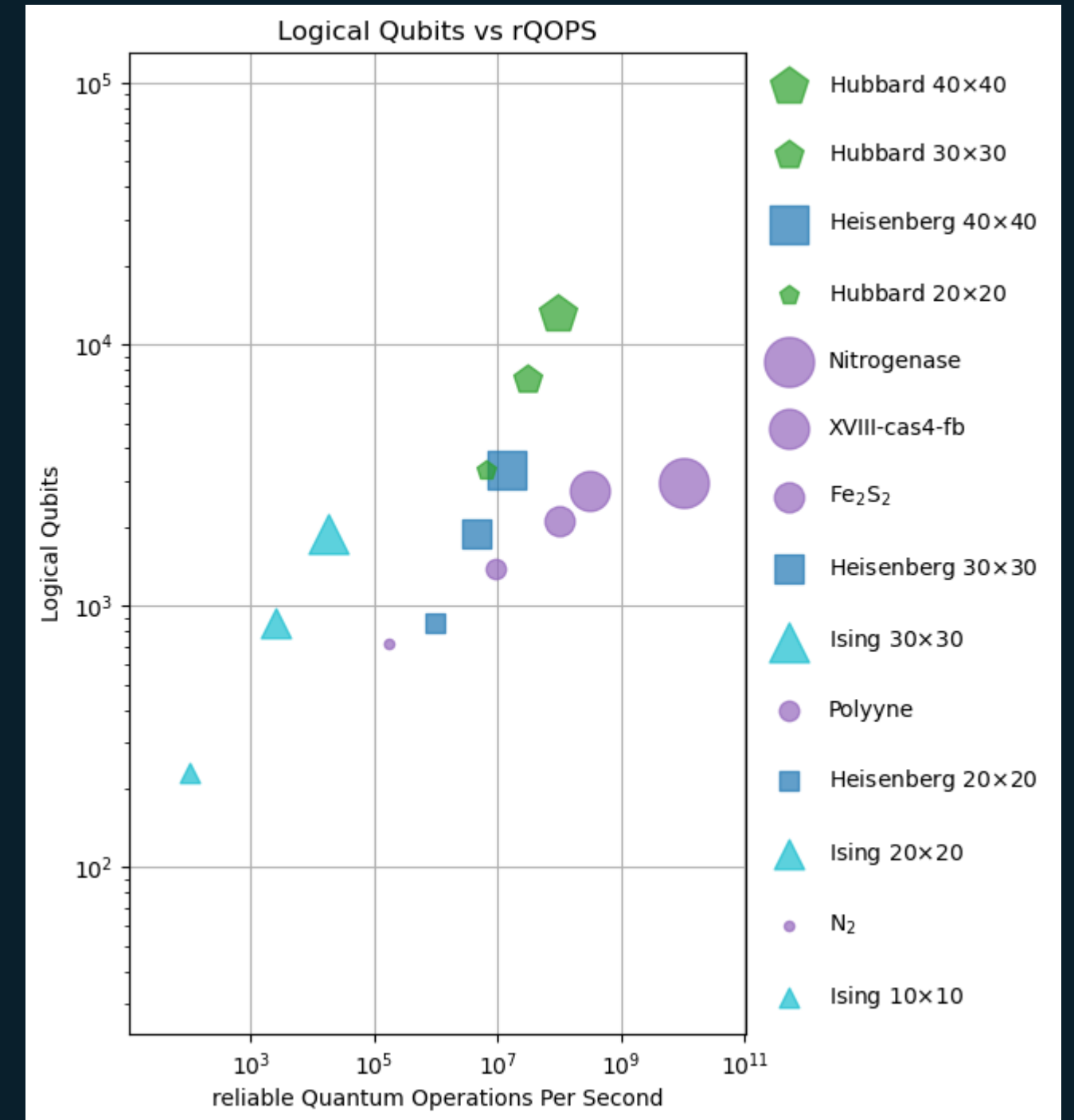


# rQOPS vs Logical Qubits vs Logical Error Rates

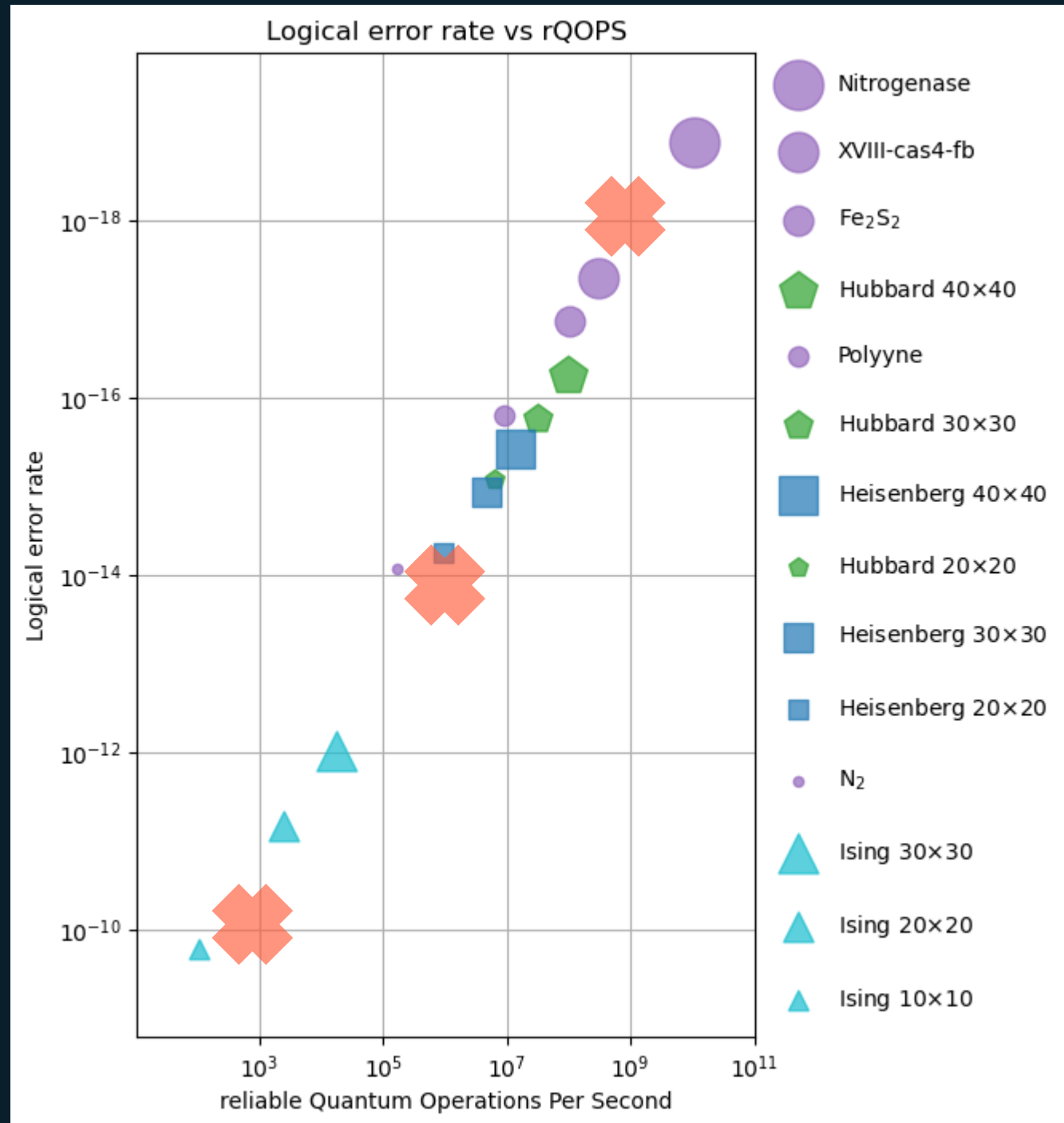


**Larger systems:**  
Logical clock-speed matters most

**Small systems:**  
Number of logical qubits matters most



# Target Profiles for kilo, Mega, and Giga rQOPS



## Giga rQOPS

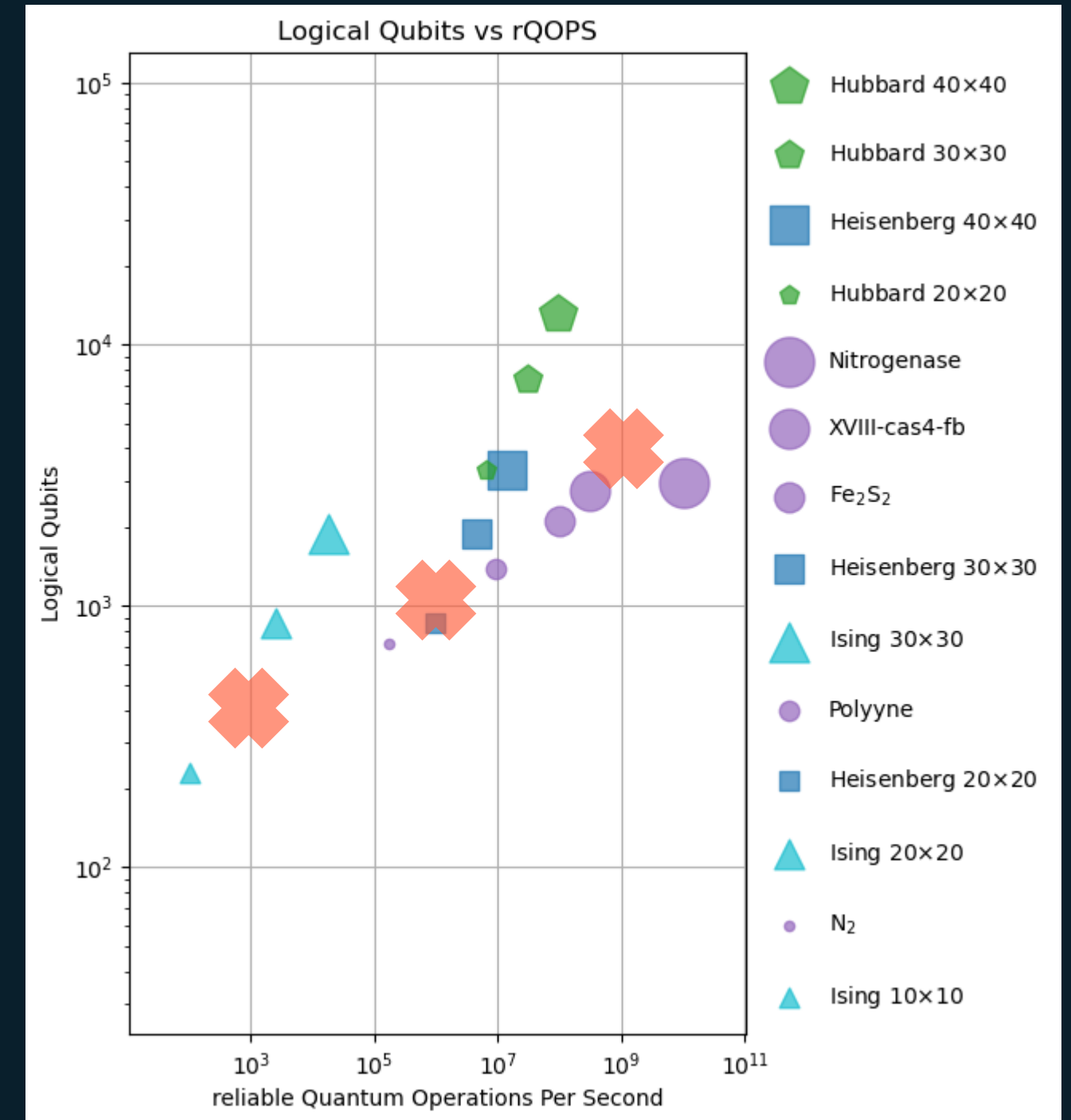
- 3000 logical qubits
- logical error  $\leq 10^{-18}$
- clock  $3.3 \times 10^5$  Hz

## Mega rQOPS

- 1000 logical qubits
- logical error  $\leq 10^{-14}$
- clock-speed  $10^3$  Hz

## kilo rQOPS

- 400 logical qubits
- logical error  $\leq 10^{-10}$
- clock-speed 2.5 Hz



# Estimating Logical Clock-Speed

$$f_{\text{logical}} = \frac{f_{\text{physical}}}{\text{QEC-overhead}}$$

## Logical clock-speed depends on

- physical clock-speed
- overhead induced by error correction
- and in turn target logical error rates

# Architecture Profiles vs Target Profiles

## kilo rQOPS:

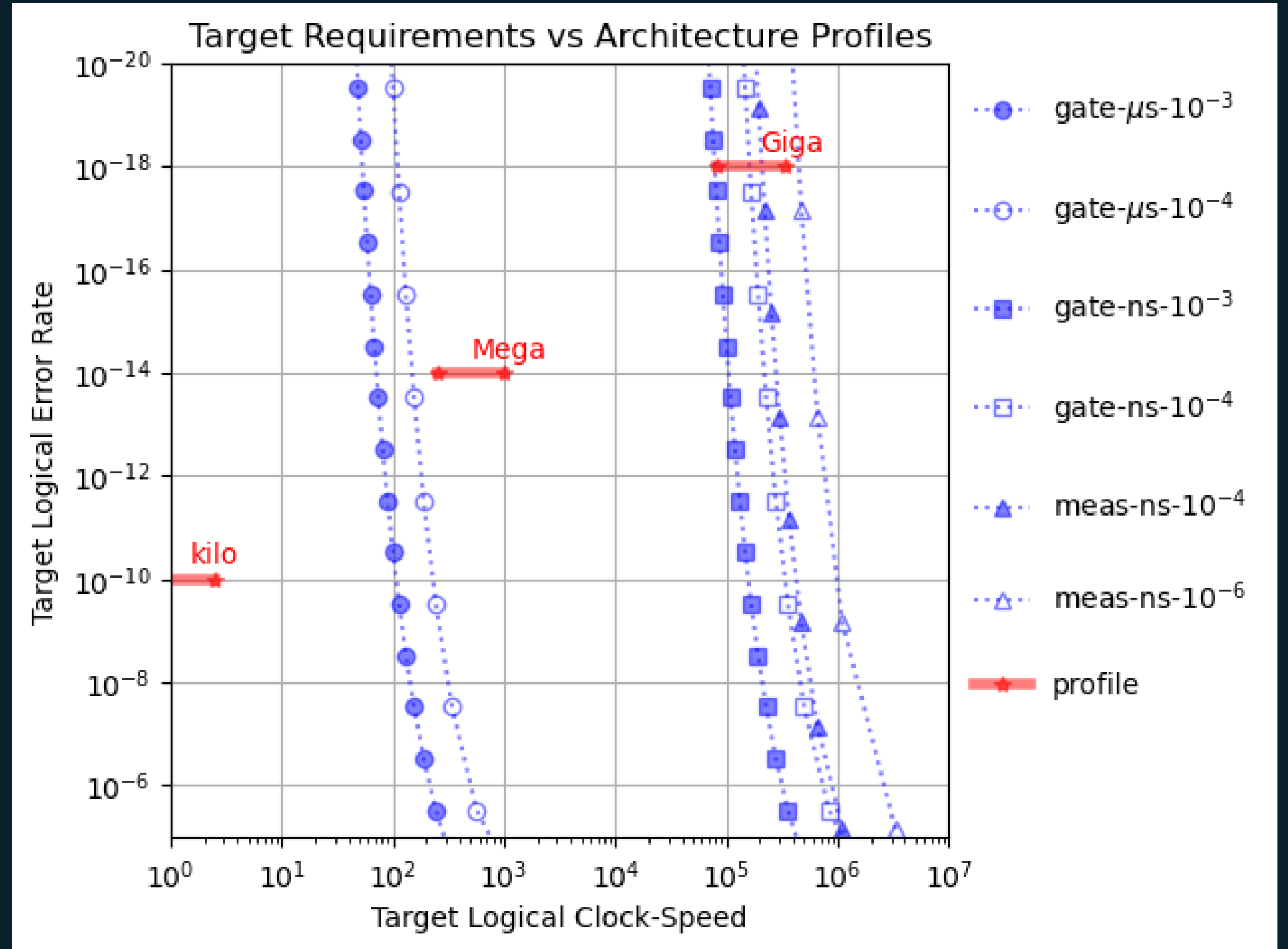
Physical clock-speed not an issue

## Mega rQOPS:

QEC slowdown starts to make a difference

## Giga rQOPS:

Physical clock-speed + fast QEC crucial



# Thank you



Try it out: [aka.ms/AQ/RE](https://aka.ms/AQ/RE)



Read about AQRE: [arXiv:2311.05801](https://arxiv.org/abs/2311.05801)  
Learn background: [arXiv:2211.07629](https://arxiv.org/abs/2211.07629)