

1 – Quantum Computing with Rydberg atoms

- Qubit logical states $|0\rangle, |1\rangle$ are two electronic levels of ^{87}Rb atom.
- Atoms can be arranged in arbitrary patterns using optical traps generated by a spatial light modulator (SLM).
- Fluorescence imaging provides global measurement, only picturing atoms in $|0\rangle$.
- In Ising mode, lasers are coupled to a Rydberg transition, between a ground $|g\rangle = |0\rangle$ and a highly-excited Rydberg state $|r\rangle = |1\rangle$.
- Ising Hamiltonian : $H = \frac{\hbar\Omega(t)}{2} \sum_i \hat{\sigma}_i^x - \hbar\delta(t) \sum_i \hat{n}_i + \sum_{i<j} \frac{C_6}{R_{ij}^6} \hat{n}_i \hat{n}_j$
with $\hat{\sigma}_i^x = |r\rangle\langle g|_i + h.c.$, $\hat{n}_i = |r\rangle\langle r|_i$, $C_6 \propto n^{11}$.
- Performing optimal control on the shape of $\Omega(t)$ and $\delta(t)$ should provide a versatile method to solve various problems.

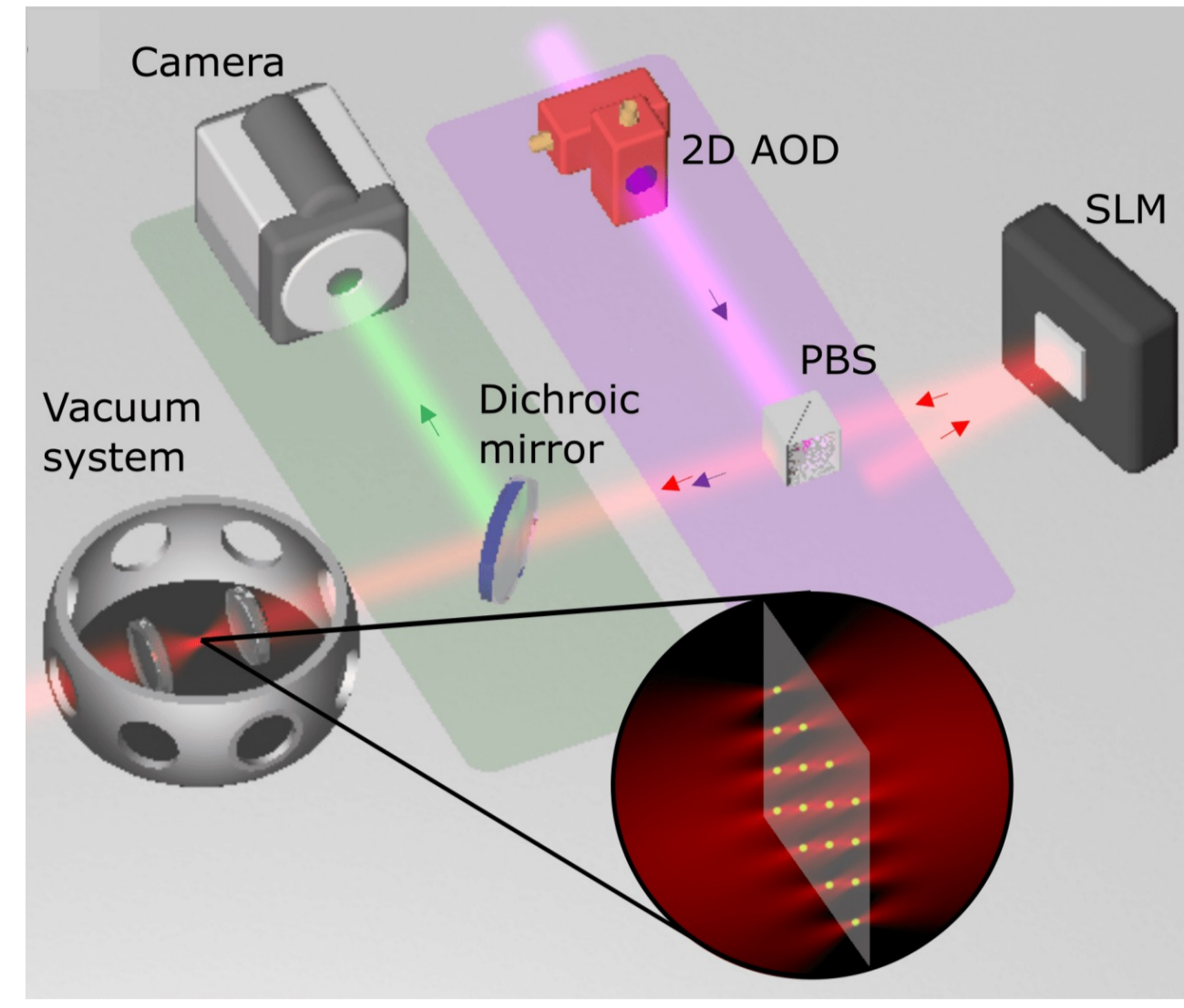


Fig. 1: Overview of the main hardware components of Pasqal QPU. [1]

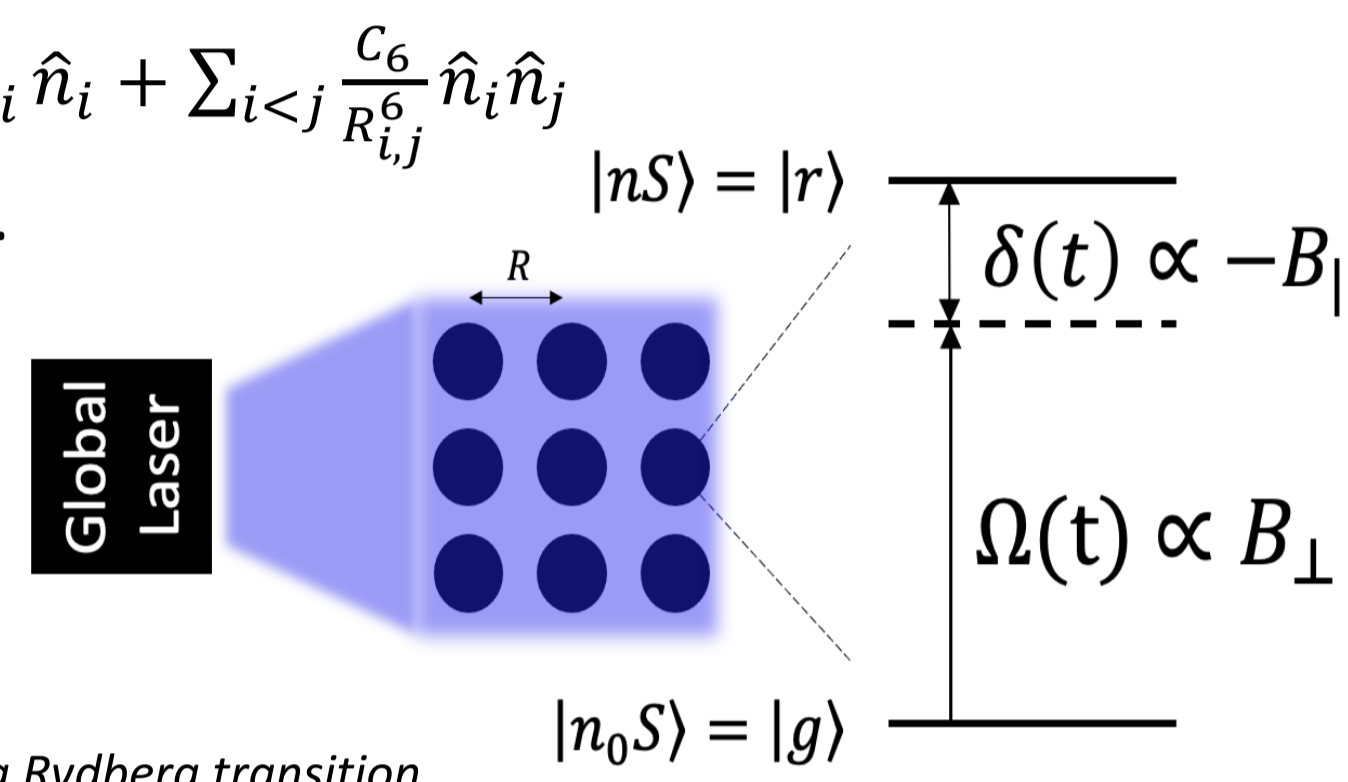
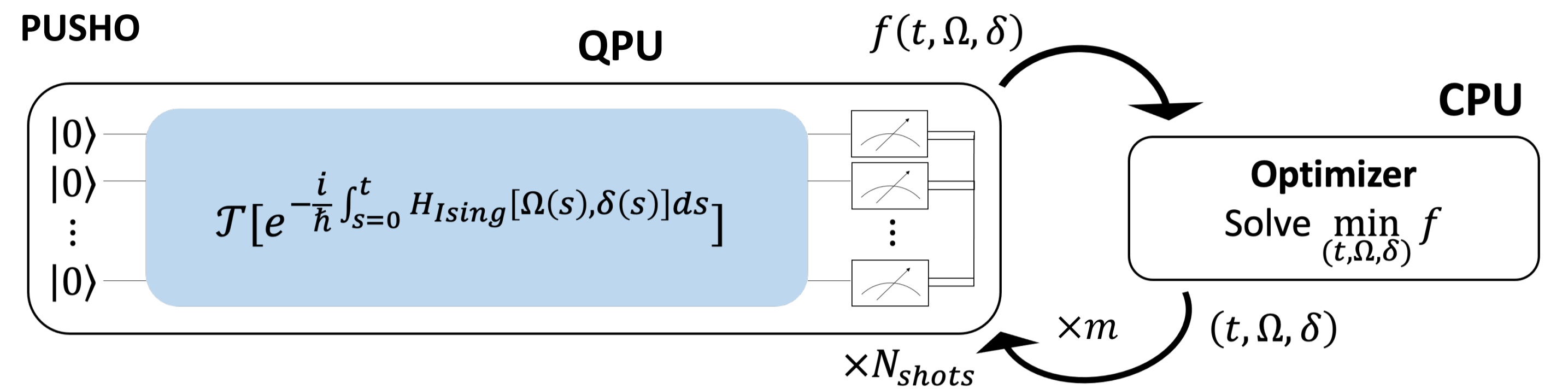


Fig. 2: Global addressing of an atom register, coupled to a Rydberg transition.

2 – Pulse Shaping Optimisation (PUSHO)

Variational Quantum Algorithms (VQA)

- Classical Processing Unit (CPU) + Quantum Processing Unit (QPU) in closed feedback loop.
- Famous QAOA [2] can approximately solve combinatorial optimisation problems which remain computationally hard to solve on CPUs alone.
- As digital approach with layers of gates, it is not well suited for current Rydberg platforms.



- Problem related objective function (score) f : average energy, overlap with target state, approx. ratio.
- Classical optimizer : Bayesian optimisation [3] works great with few iterations (small n) on low-dimensional parameter space.
- Pulse shaping : $\{t, \Omega(t_i), \delta(t_i)\}$ + interpolation by monotonic cubic splines.
- PUSHO = VQA closer than QAOA to Rydberg platforms, with smoother and shorter pulses.

Fig. 3: Closed loop between CPU & QPU. The optimizer feeds the quantum device a pulse to test. Once the driving has been repeated N_{shots} times, the score evaluation is fed back to the optimizer which will decide the next point to probe.

3.1 – State Preparation

Initial States

- Atoms all initialised in $|g\rangle$ and only global addressing available.
- Some problems need to start from specific states, e.g. $|+\rangle^{\otimes N}$ or antiferromagnetic (AF) phases.

AF state on periodic chain

- AF : neighbouring atoms are in opposite states.
- Score : Neel structure factor, maximised for AF state.
- PUSHO provides adiabatic pulses, smoother than typical ramp. $S_{Neel}/S_{max} = 0.98$

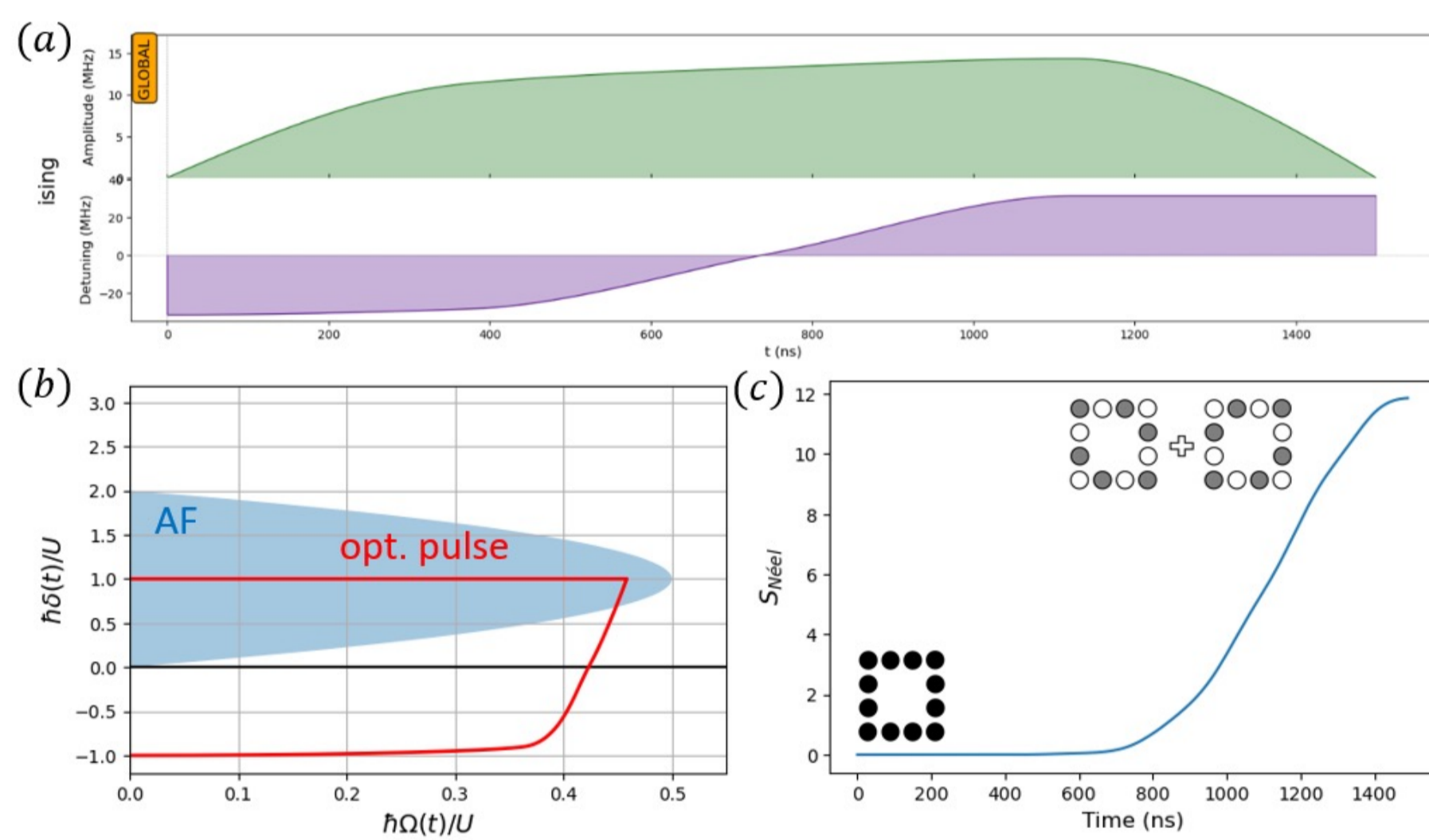


Fig. 4 : (a) Optimal pulse found after 30 iterations. (b) Optimal path in 1D phase diagram [4] (c) Increase of structure factor shows AF phase transition.

Uniform superposition

- No local gate available, global pulse required.
- PUSHO increases fidelity by 27% over a global Blackman pulse.

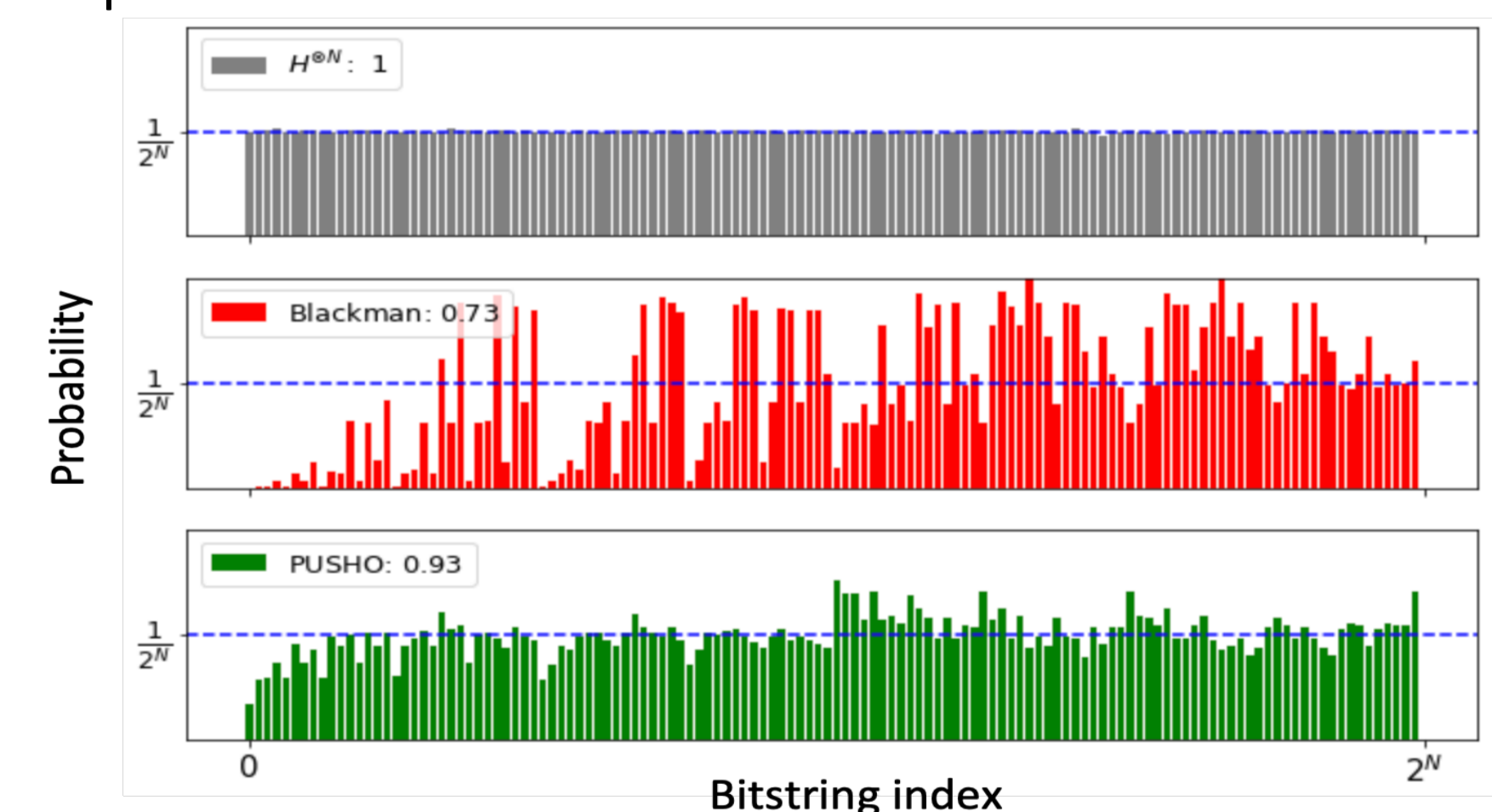
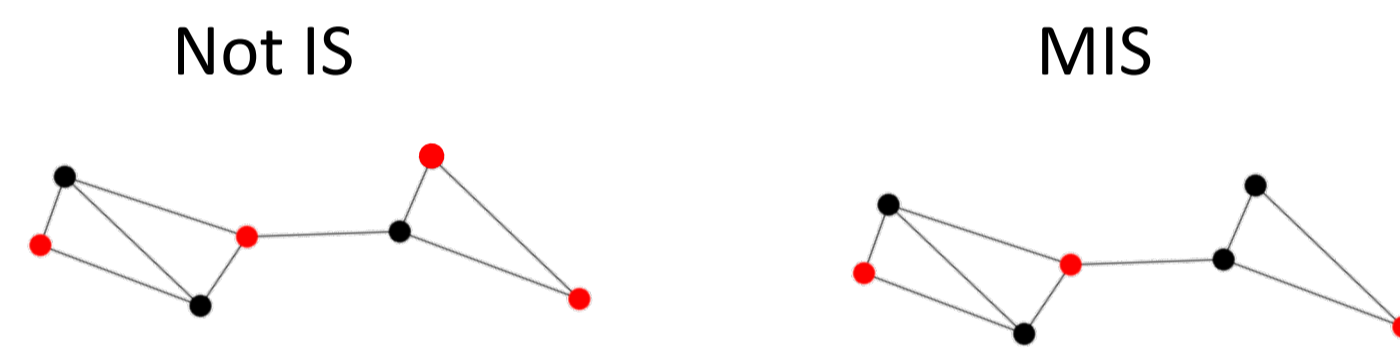


Fig. 5 : Distributions after (top) N simultaneous perfect Hadamard gates, (middle) global Blackman pulse (250 ns, 2 MHz) and (bottom) optimised pulse (160 ns, 2 MHz) for triangular lattice of 10 atoms separated by $8.5\mu\text{m}$.

3.2 – UD MIS

Maximum Independent Set

- Graph $G = (V, E)$ with V , vertices and E , edges.
- Independent Set (IS) : set of vertices in a graph, no two of which are sharing an edge.



- NP-hard problem to find an IS of maximum size (MIS).
- Even harder to find all MIS of a graph.

Formalism

- 1 atom = 1 node of a Unit Disk (UD) graph (edge if $d_{ij} < d$).
- Rydberg blockade implements the IS constraint.
- MISs correspond to product states with as many excitations as allowed [5].

$$\hat{C} = -\sum_{i \in V} \hat{n}_i + K \sum_{(i,j) \in E} \hat{n}_i \hat{n}_j$$

with $K \gg 1$.

$$r = \frac{\sum_{n=1}^{N_{shots}} \langle n | \hat{C} | n \rangle}{N_{shots}}$$

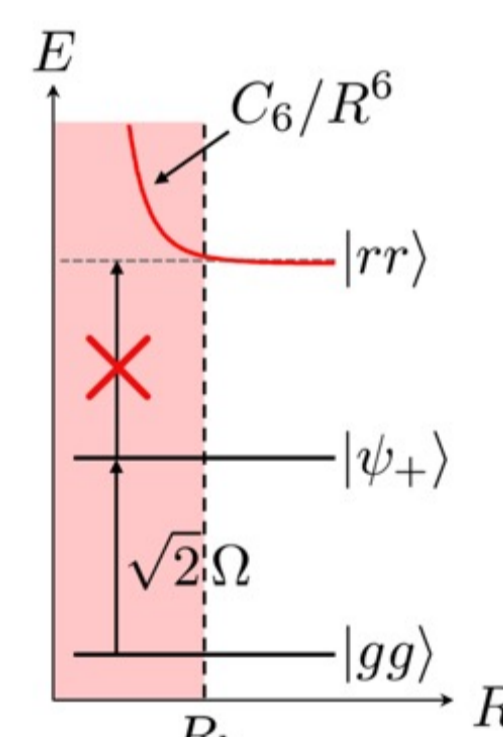


Fig. 6 : Diagram showing Rydberg blockade effect.

Results

- \mathcal{G} dataset of 50 randomly generated UD graphs of 15 atoms
- Average ratio on \mathcal{G} reaches 0.92 for large m .

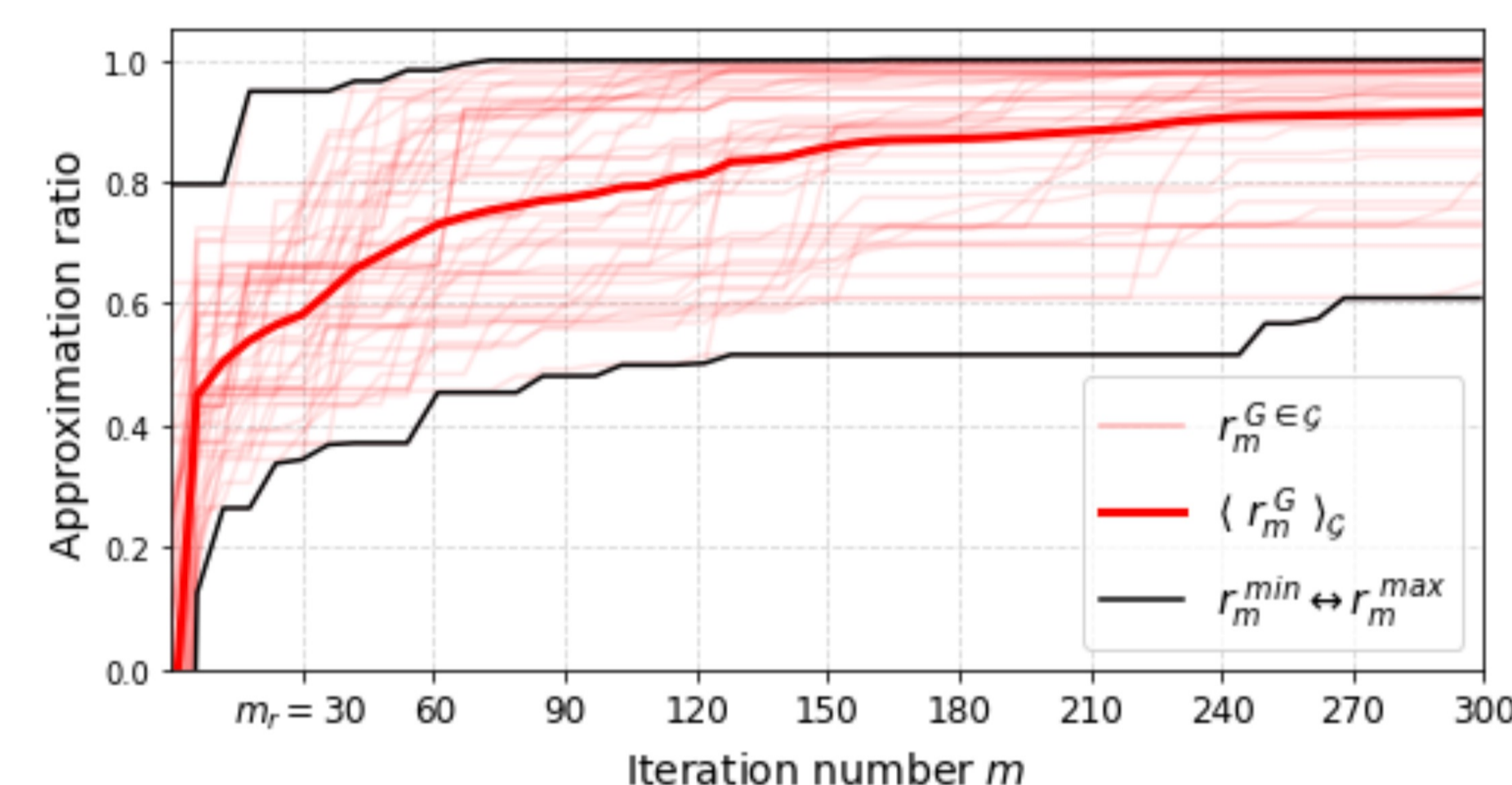


Fig. 7 : Convergence study of PUSHO on UD graph dataset \mathcal{G} . After $m_r = 30$ random calls to learn about the score landscape, Bayesian optimisation iteratively provides new pulses to test. Already after 150 calls, the mean ratio achieved is 0.87.

3.3 – QUBO

Quadratic Unconstrained Binary Optimisation

- $Q \in M_n(\mathbb{R})$, find $x^* \in \mathbb{B}^n$ minimising $f_Q(x) = x^T Q x$.
- Many problems can be embedded as QUBOs [6].
- Study symmetric case with $h_{ii} = Q_{ii} \leq 0$ and $Q_{ij} \geq 0$.
- Connection with Ising model but limited by connectivity.

Formalism

- $\hat{C} = -\sum_i h_i \hat{n}_i + \sum_{i \neq j} Q_{ij} \hat{n}_i \hat{n}_j$
- Optimally arrange atoms such that $C_6/R_{ij} \sim Q_{ij}$.
- Choose $\delta \sim h$ and $\Omega \sim \max_{i \neq j} Q_{ij}$.
- Start from uniform superposition of states (using PUSHO).
- Approx. ratio as defined in MIS part.

Results

- For 5 $Q \in M_{10}$, PUSHO outperforms QAOA with pulses of similar duration and amplitude.

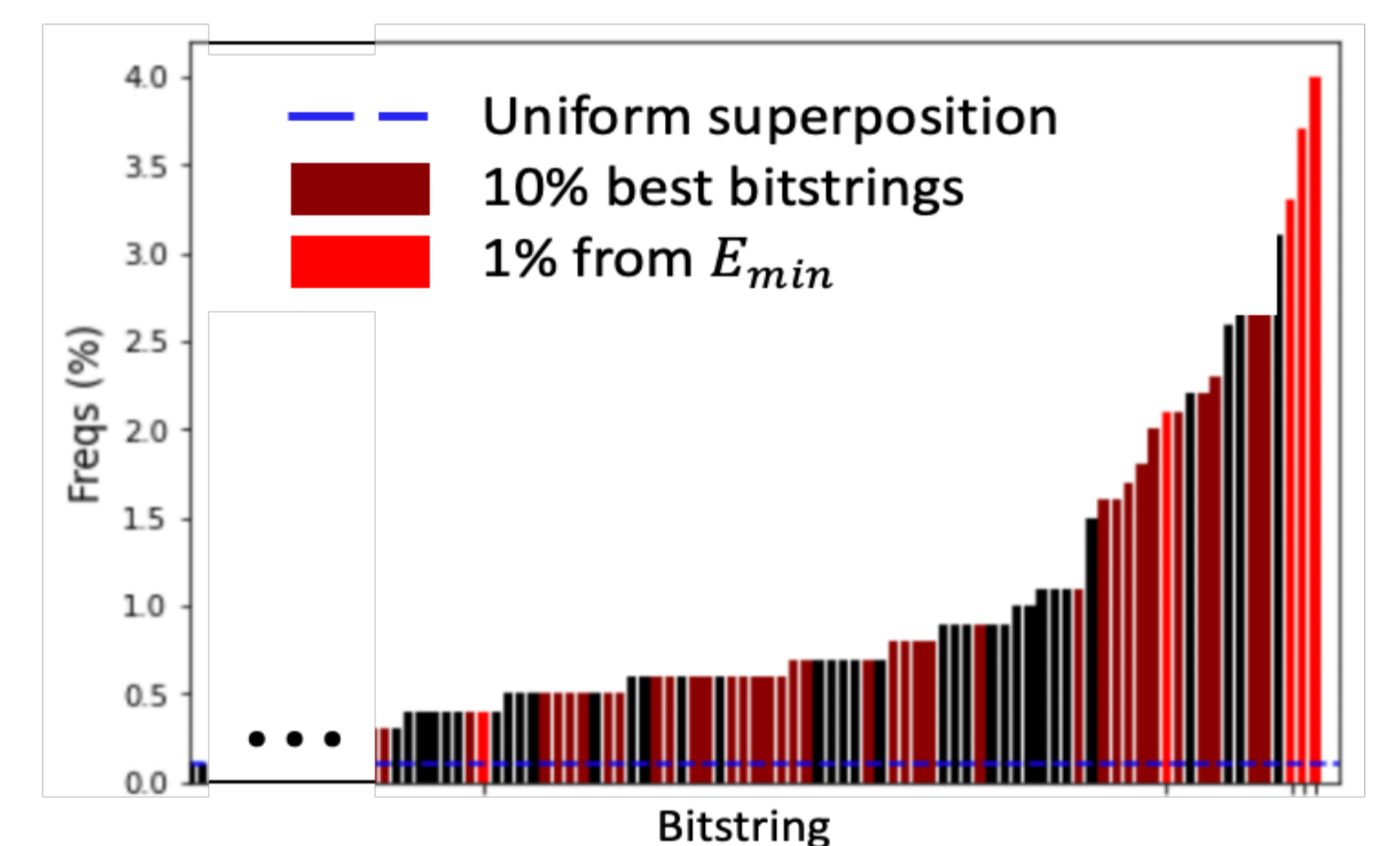


Fig. 8 : Instance of distribution obtained after an optimised pulse. Bitstrings sampled most frequently are of energy very close to the minimum one.

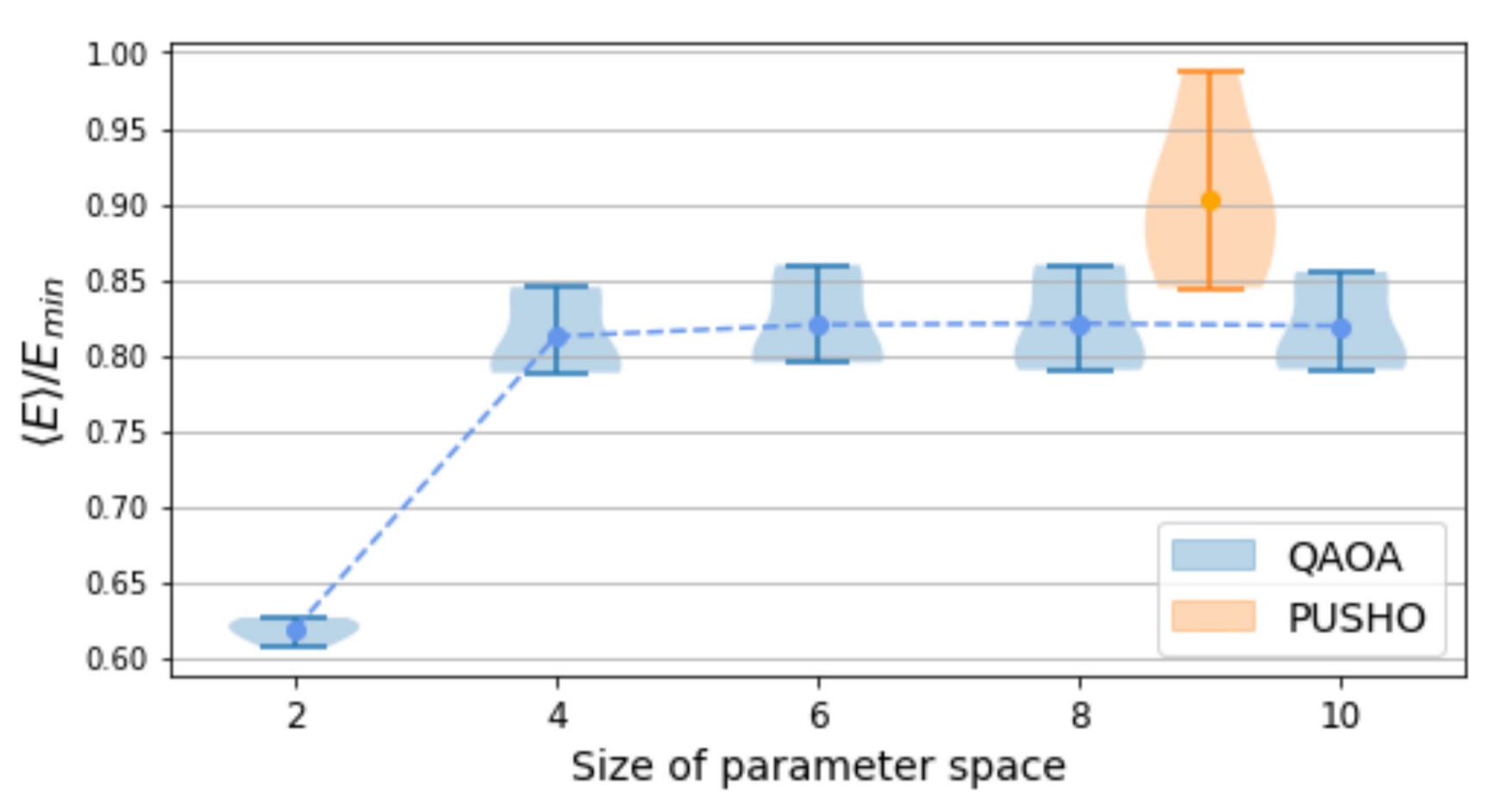


Fig. 9 : Comparison between QAOA and PUSHO. Distribution achieved with PUSHO outperforms the one QAOA converges to, even with higher-dimensional space.

4 – Conclusion & Outlooks

- PUSHO provides a straightforward but powerful alternative to QAOA, taking advantage of our ability to precisely control the shape of the driving fields.
- In all the above cases, the final score reached with PUSHO is always higher than the one found with QAOA, for similar optimization conditions.
- In the presence of noise Δ , PUSHO can also improve the average score $\langle S \rangle_\Delta$ by providing a more resilient pulse than square pulses (Master thesis)



References

- Henriët, L., Beguin, L., Signoles, A., Lahaye, T., Browaeys, A., Raymond, G.O., and Jurczak, C. (2020). Quantum computing with neutral atoms. *Quantum*, 4, p.327.
- Farhi, E., Goldstone, J., Gutmann, S. (2014). A Quantum Approximate Optimization Algorithm.
- Peter I. Frazier. (2018). A Tutorial on Bayesian Optimization.
- Lienhard, A. et al. (2018). Observing the Space- and Time-Dependent Growth of Correlations in Dynamically Tuned Synthetic Ising Models with Antiferromagnetic Interactions. *Phys. Rev. X*, 8, p.021070.
- Minhyuk Kim, Kangheun Kim, Jaeyong Hwang, Eun-Gook Moon, and Jaewook Ahn. (2021). Rydberg Quantum Wires for Maximum Independent Set Problems with Nonplanar and High-Degree Graphs.
- Kochenberger, G., Glover, F., and Zaslavski, A. (1970). A Unified Framework for Modeling and Solving Combinatorial Optimization Problems: A Tutorial.