

# Testing the operation of the QAOA algorithm on the quantum testbed of the HybriLIT platform

*Yu. Paliy\*, A. Bogolubskaya, D. Yanovich*

Joint Institute for Nuclear Research, Dubna, Russia

\* Institute of Applied Physics, Chisinau, Moldova

MPQIT'2024

Dubna, May 27-28 2024

## Variational Quantum Algorithms

VQA (gate based) are hybrid quantum-classical algorithms, which employ a **short-depth quantum circuit** to efficiently evaluate a cost function depended on the parameters of a quantum gate sequence, and then leverage classical optimizers to minimize this cost function.

**Quantum mechanical variational principle (Rayleigh-Ritz):**

for any parametrized trial wave-function (state vector)  $|\psi(\alpha)\rangle$ ,  $\alpha = (\alpha_1, \dots, \alpha_n)^T$

$$\langle \psi(\alpha) | \mathcal{H} | \psi(\alpha) \rangle \geq E_{Ground}.$$

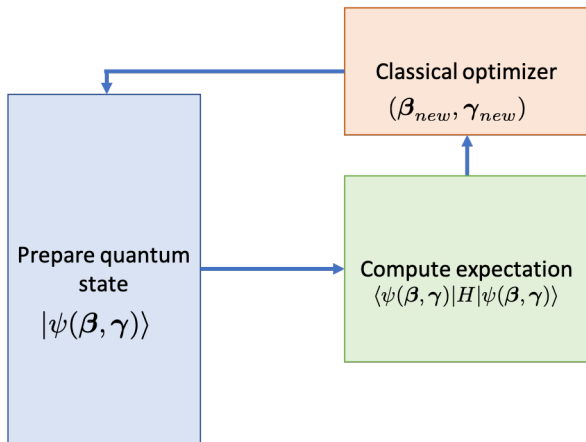
The expectation value of the Hamiltonian plays the role of the cost function.

Edward Farhi and Jeffrey Goldstone. ArXiv:1411.4028

*A Quantum Approximate Optimization Algorithm (QAOA)*

produces approximate solutions for combinatorial optimization problems.

## General Scheme of Variational Quantum Algorithms



Computation loop:

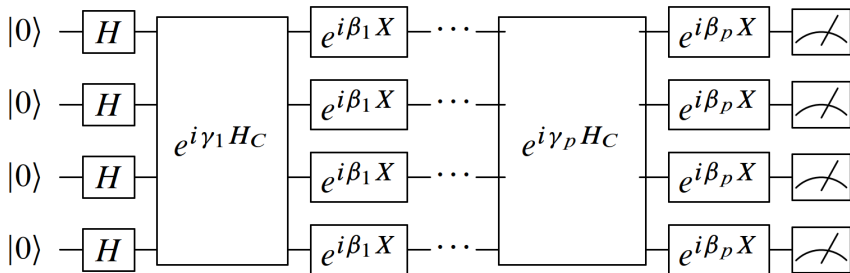
**quantum computer** : prepare  $|\psi(\gamma, \beta)\rangle$  and measure observables,

**classical computer** : update the parameters  $\gamma, \beta$  with an optimization algorithm to reduce the expectation value of the cost Hamiltonian.

## QAOA Variational Ansatz $|\psi(\gamma, \beta)\rangle$

The driver  $U(\gamma_i, \mathcal{H})$  and mixing  $U(\beta_i, B)$ ,  $i = 1, \dots, p$ , operators are arranged in  $p$  layers.

$$|\psi(\gamma, \beta)\rangle = \underbrace{U(\beta_p, B)U(\gamma_p, \mathcal{H}) \dots U(\beta_1, B)U(\gamma_1, \mathcal{H})}_p H^{\otimes n} |0\rangle^{\otimes n}$$



## Main QAOA Theorem

$$\lim_{p \rightarrow \infty} \min_{\gamma, \beta} E_p(\gamma, \beta) = E_{\text{Ground}}, \quad E_p(\gamma, \beta) \equiv \langle \psi(\gamma, \beta) | \mathcal{H} | \psi(\gamma, \beta) \rangle$$

## Ising model Hamiltonian using Pauli strings

Ising Hamiltonian with nearest-neighbor interaction in an external magnetic field  $h$ :

$$\mathcal{H}(Z) = -J \sum_{\langle i,j \rangle} Z^{(i)} Z^{(j)} - h \sum_i Z^{(i)}$$

$Z^{(i)} = \mathbb{I} \otimes \dots \otimes Z \otimes \dots \otimes \mathbb{I}$  Pauli operator  $Z$  on  $i$ -th position acts on  $i$ -th qubit

### Variational Problem:

find the spin configuration on the lattice with the lowest expectation value of  $H(Z)$ , i.e. energy  $E = \langle \psi(\alpha) | \mathcal{H} | \psi(\alpha) \rangle$ , varying the set of parameters  $\alpha$ .

## Operators for construction of QAOA Variational Ansatz $|\psi(\gamma, \beta)\rangle$

- Driving operator with the Hamiltonian  $\mathcal{H}(Z)$  (commutativity of the Hamiltonian terms is used the factorization),

$$\begin{aligned} U(\gamma, \mathcal{H}) &= e^{i\pi\gamma\mathcal{H}(Z)/2} \\ &= \prod_{\langle i,j \rangle} \exp\left(-i\pi J\gamma Z^{(i)} \cdot Z^{(j)}/2\right) \text{ (ZZ interaction of the neighbours } i \text{ and } j), \\ &\quad \prod_i \exp(-i\pi\gamma h Z^{(i)}/2) \text{ (interaction of } i\text{th site with the magnetic field)}. \end{aligned}$$

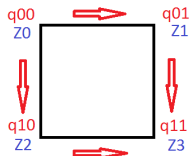
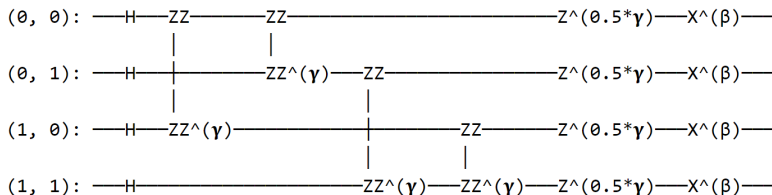
- Mixing operator with Pauli- $X$  operators,

$$U(\beta, B) = e^{i\pi\beta B(X)/2} = \prod_{j=1}^n e^{i\pi\beta X_j/2}, \quad B(X) = \sum_{j=1}^n X_j.$$

The variational parameters  $\gamma$  and  $\beta$  are “evolution times”.

## The Quantum Circuit for the Variational Ansatz $|\psi(\gamma, \beta)\rangle$

one layer,  $p = 1$ ,  $J = 1$ ,  $h = 0.5$  prepared with Google package Cirq (Python).



Search in Parameter Space using the direct access to the state vector  $|\psi(\gamma, \beta)\rangle$ .

- One-layer Variational Ansatz

$$|\psi(\gamma, \beta)\rangle = U(\beta, B)U(\gamma, \mathcal{H})H^{\otimes 4}|0\rangle^{\otimes 4}$$

- Energy as expectation value of the Hamiltonian is a function of the variational parameters  $\gamma, \beta$ ,

$$E(\gamma, \beta) = \langle \psi(\gamma, \beta) | \mathcal{H} | \psi(\gamma, \beta) \rangle,$$

or, if we use the diagonal form of the Hamiltonian,

$$E(\gamma, \beta) = \sum_{i=0}^{2^4-1} |\alpha_i(\gamma, \beta)|^2 E_i.$$

QAOA ansatz (parametrized state vector describing the quantum register)

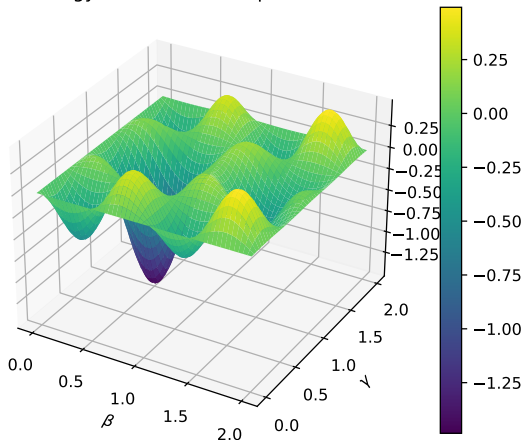
$$|\psi(\gamma, \beta)\rangle = \alpha_0(\gamma, \beta)|0000\rangle + \alpha_1(\gamma, \beta)|0001\rangle + \dots + \alpha_{15}(\gamma, \beta)|1111\rangle$$

Energy per site for each spin configuration (main diagonal of  $\mathcal{H}$ )

$$E = [-1.5, -0.25, -0.25, 0, -0.25, 0, 1, 0.25, -0.25, 1, 0, 0.25, 0, 0.25, 0.25, -0.5]$$



## Energy as a function of parameters

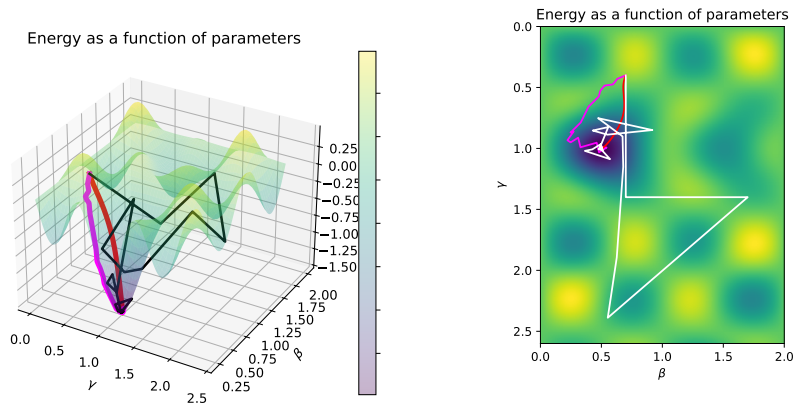


Learned optimal values  $\gamma = 1.0$ ,  $\beta = 0.5$ .

define the state vector  $|\psi(\gamma, \beta)\rangle = [\alpha_0(\gamma, \beta) \approx -0.999, 0, \dots, 0]$ ,  
which corresponds to the basis vector  $|0000\rangle$

providing the minimal value  $E(\gamma = 1.0, \beta = 0.5) = E_{min} = -1.5$ .

## Minimization in 2-dim Parameter Space for $2 \times 2$ lattice.



Minimization trajectories:

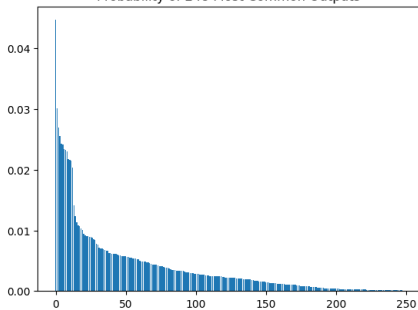
- red curved arrow, gradient optimization;
- magenta broken line, gradient-free optimization (Nelder - Mead, simplex method);
- black and white broken lines (COBYLA, simplex method).

## One-layer Ansatz for $2 \times 2 \times 2$ lattice. Sampling (register state measurement).

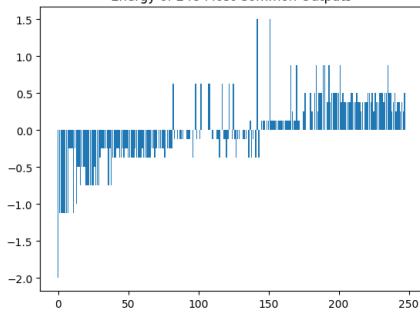
Sampling data for a set of  $n_{meas} = 10000$  measurements at the point  $(\gamma, \beta) = (0.8, 1.2)$ :

output enumeration	0	1	2	...	248
basis state	$ 00000000\rangle$	$ 00001000\rangle$	$ 10000000\rangle$	...	$ 10010011\rangle$
occurrences, $n_{state}$	447	301	269	...	1
energy, $E_{state}$	-2.0	-1.125	-1.125	...	0.5

Probability of 248 Most Common Outputs



Energy of 248 Most Common Outputs



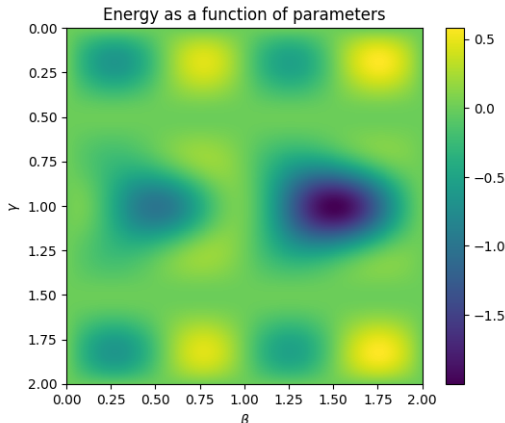
$$E_1^{Sampl}(0.8, 1.2) = \sum_{states} E_{state} n_{state} / n_{meas} = -0.5187 \text{ vs } E_1^{State Vctor}(0.8, 1.2) = -0.5184$$

## 2x2 lattice. One-layer Ansatz. Sampling Search in Parameter Space

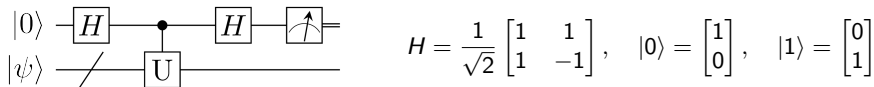
Energy evaluation with sampling data instead of direct using of  $|\psi(\vec{\gamma}, \vec{\beta})\rangle$ .

$$E_p(\gamma, \beta) \approx \sum_{i=0}^{n-1} \mathcal{P}_{i,p}(\gamma, \beta) E_i, \quad \sum_{i=0}^{n-1} \mathcal{P}_{i,p}(\gamma, \beta) = 1, \quad \mathcal{P}_{i,p}(\gamma, \beta) = n_{i\text{th state}} / n_{\text{meas}}$$

where  $\mathcal{P}_{i,p}(\gamma, \beta)$  is the probability to find the register in  $i$ -th basis state (with energy  $E_i$ ) given  $p$ -layer ansatz and a fixed set of the parameters  $\vec{\gamma}, \vec{\beta}$ .



## Evaluation of an average $\langle \psi(\alpha) | U | \psi(\alpha) \rangle$ . Hadamard Test



$$\begin{aligned} |0\rangle \otimes |\psi\rangle &\xrightarrow{H} \frac{1}{\sqrt{2}} (|0\rangle \otimes |\psi\rangle + |1\rangle \otimes |\psi\rangle) \\ &\xrightarrow{\text{contr}-U} \frac{1}{\sqrt{2}} (|0\rangle \otimes |\psi\rangle + |1\rangle \otimes U|\psi\rangle) \\ &\xrightarrow{H} \frac{1}{2} \left( (|0\rangle + |1\rangle) \otimes |\psi\rangle + (|0\rangle - |1\rangle) \otimes U|\psi\rangle \right) = \\ &= \frac{1}{2} \left( (|0\rangle \otimes (\mathbb{I} + U)|\psi\rangle + |1\rangle \otimes (\mathbb{I} - U)|\psi\rangle) \right) \end{aligned}$$

Measurements of the ancilla qubit  $|0\rangle$  allow to evaluate the average  $\langle \psi | U | \psi \rangle$ .

$$P(1) = \frac{1}{2} \langle \psi(\alpha) | (\mathbb{I} - \text{Re } U) | \psi(\alpha) \rangle, \quad P(0) = 1 - P(1) = \frac{1}{2} \langle \psi(\alpha) | (\mathbb{I} + \text{Re } U) | \psi(\alpha) \rangle$$

$$\text{Re } \langle \psi(\alpha) | U | \psi(\alpha) \rangle = 1 - 2P(1), \quad 2\text{Re } U = U + U^\dagger$$

Evaluation an average  $\langle \psi(\alpha) | U | \psi(\alpha) \rangle$  needs measuring only the ancilla qubit!

# Optimization

SciPy optimize

We fulfilled minimization with two parameters (one-layer ansatz) and six parameters (three-layer ansatz).

## Local (multivariate) optimization

Direct search algorithms (gradient-free optimization). Gradient-based failed.

COBYLA, Powell, Nelder-Mead

## Global optimization

(Typically, global minimizers efficiently search the parameter space, while using a local minimizer (e.g., minimize) under the hood.)

- Dual Annealing (with COBYLA and Powell as local minimizers),
- SHGO (simplicial homology global optimization) with COBYLA and Powell.  
*sampling\_method='sobol'*.

Computations with large number of qubits (e.g. Ising model on  $3 \times 3 \times 3$  lattice, 27 qubits) become time and memory consuming.

The situation is especially hard for the schemes with the Hadamard test and when the number of repetitions for sampling is large.

**Solution: the quantum testbed of the HybriLIT platform**

**Полигон для квантовых вычислений**

<http://hlit.jinr.ru/quantum-polygon/>