Performance Analysis and Comparative Study of QAOA Variants

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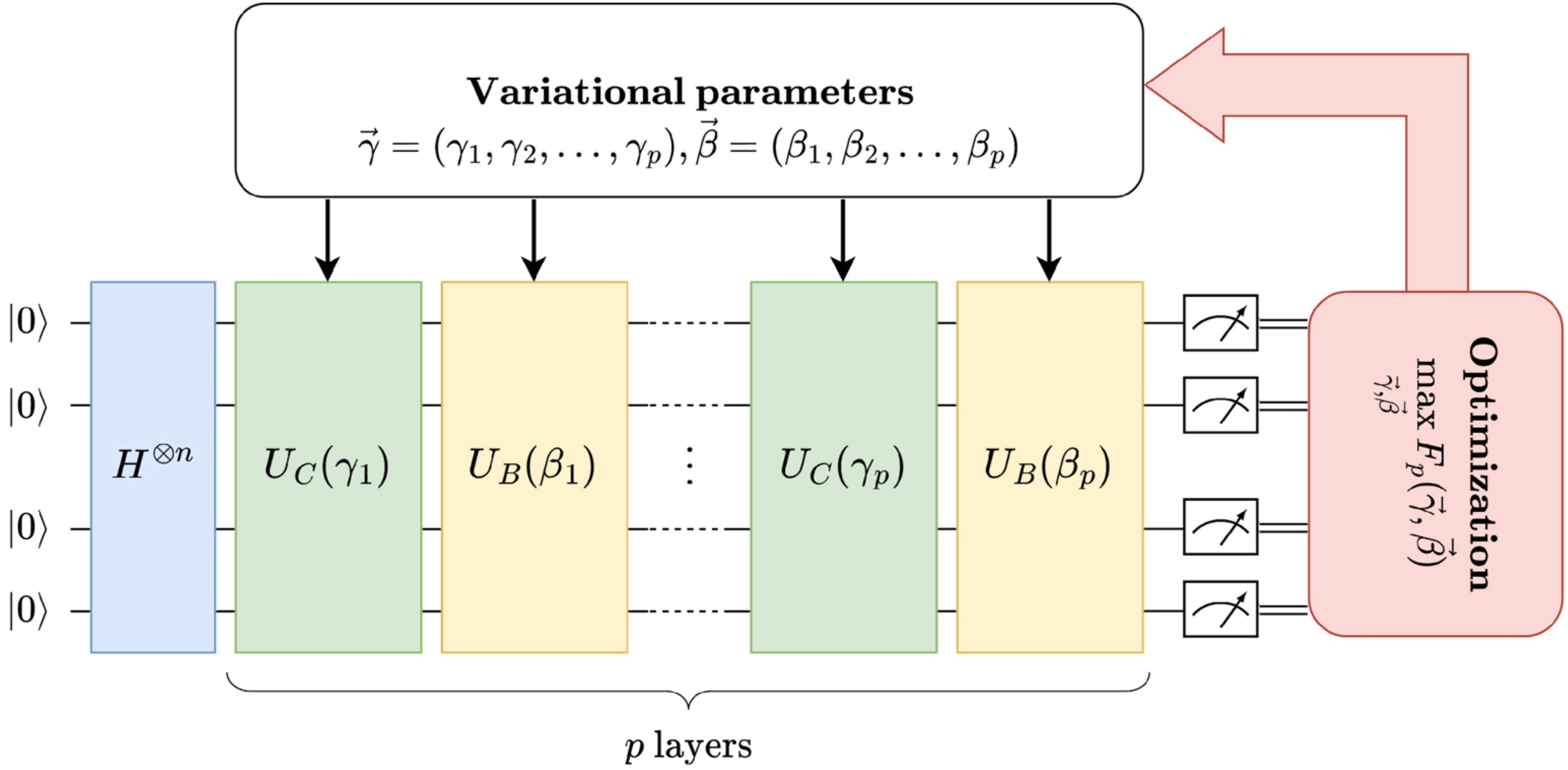
QAOA: Problem-inspired ansatz

- Inspired by Trotterized AQC, QAOA was designed to be a variational algorithm with repeated cost and mixer layers.



QAOA

- Layerized variational form based on trotterization of an adiabatic process.

$$H = sH_c + (1 - s)H_M$$

$$\left(e^{\alpha H_C} e^{\beta H_M}\right)^n$$

QAOA Evaluation

- Guaranteed solution using infinite steps.

- In general* QAOA slightly underperforms compared to classical algorithms

$$75\% < 88\%$$

QAOA Variations

Improve Resource Use

- Reduce number of parameters
- Improve initial guess
- ...

Improve Approximation Ratio

- Specialize ansatz for problem
- Improve optimization strategy
- ...

Extend to other problems
e.g constrained

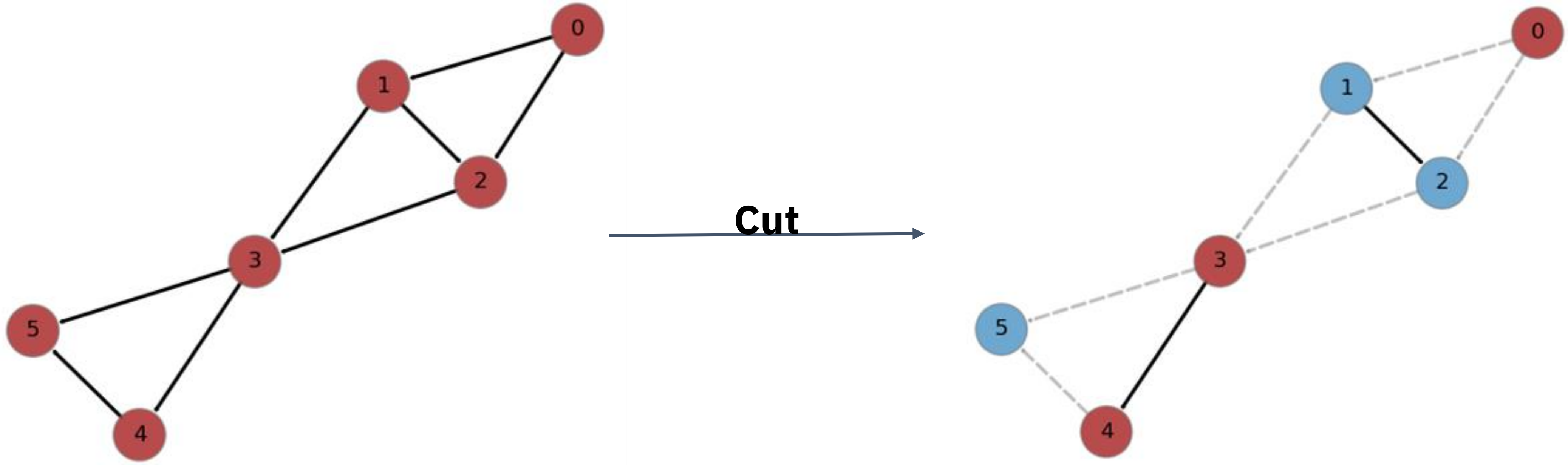
Improve Noise Resilience

Variations landscape

Variant	MA- QAOA	QAOA+	DC-QAOA	ab-QAOA	ADAPT-QAOA	RQAOA	QAOAnsatz	GM-QAOA	Th-QAOA	Constraint Preserving Mixers	WS-QUA	FALQON	FQAOA
Efficiency	± / +	± / ±	± / +	± / +	± / ±	± / ±	- / +	± / +	± / ±	± / +	+/±	- / +	± / ±
Solution Quality	+	+	±	+	+	+	+	+	+	±	+	±	+
Complexity	-	±	-	±	-	-	-	±	±	±	±	+	-
Constraints Handling	±	±	±	±	±	±	+	+	±	+	±	±	+
Noise Resilience	±	±	+	±	±	±	±	+	±	±	±	±	±

MaxCut problem

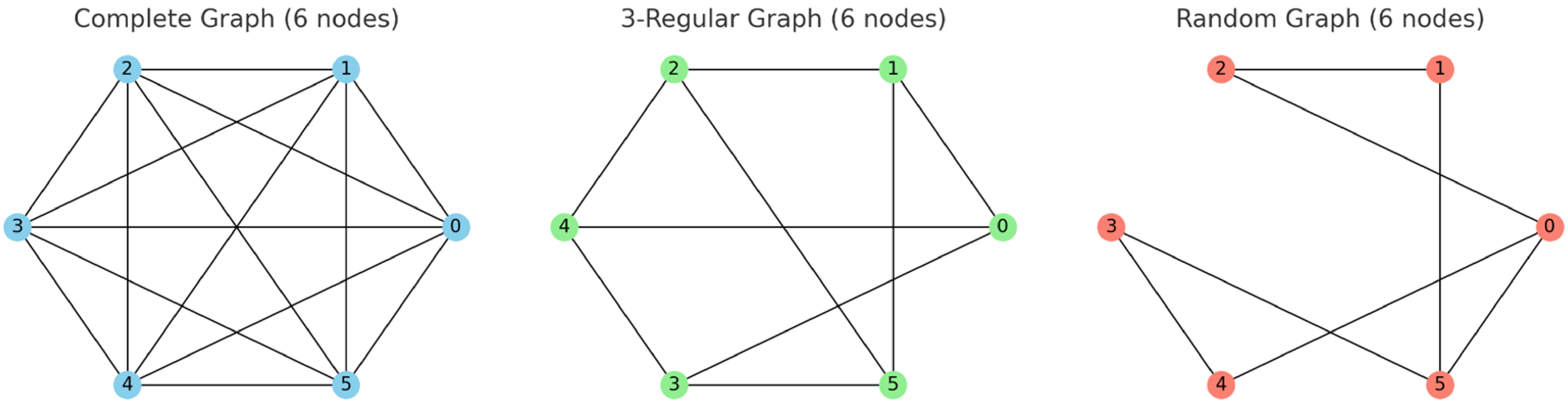
- Partition ("cut") a graph in two groups, maximizing the interconnection between them.



- Lots of practical applications.
- Adaptable (changing graph type and connectivity significantly changes the problem).
- NP-Hard.

QAOA variants evaluation and comparison

- Complete, 3-regular and random graphs; 4 to 24 nodes; 8 variations
- 8 QAOA variants; 1 to 8 layers
- Noise-free (simulations) and noisy (IBM quantum devices)



QAOA variants evaluation and comparison

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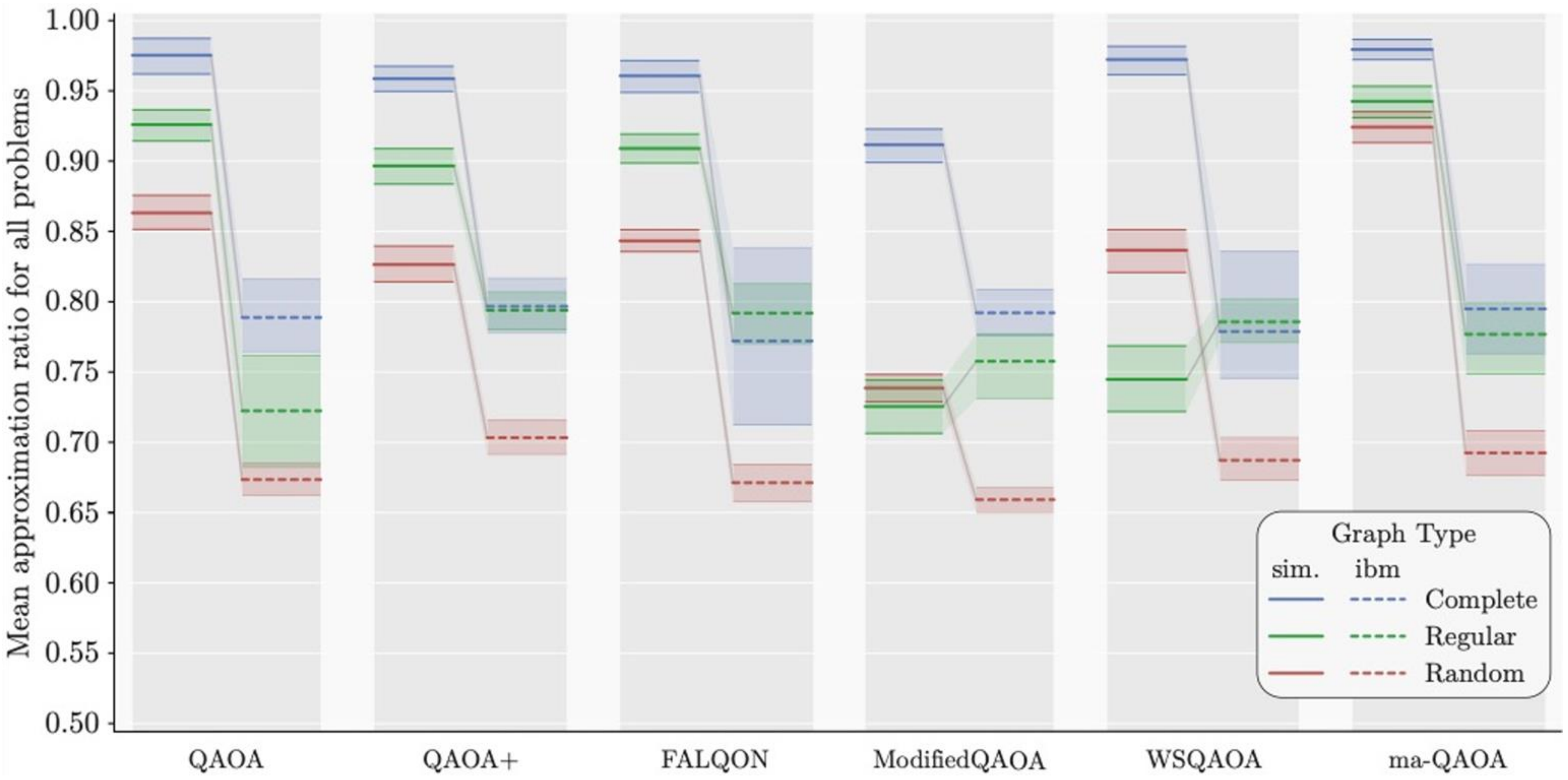
Problem Type	Variations per Node Size	Node Sizes (Even 4-24)	Layers (1-8)	Total Variations
Complete Graphs	1	11	8	88
3-Regular Graphs	8	11	8	704
Random Graphs	8	11	8	704

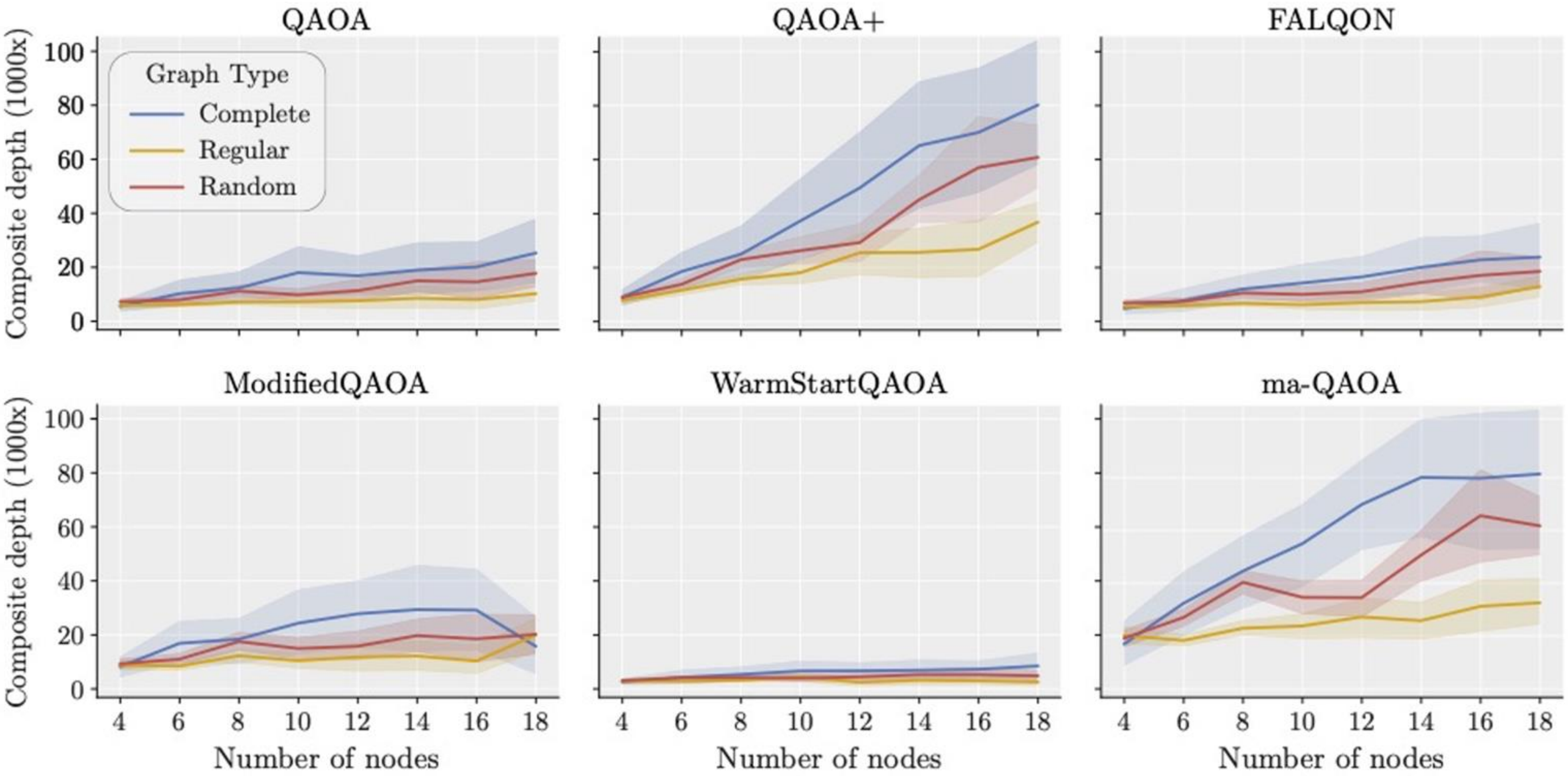
Problem type vs approximation ratio

- The problem type (graph connectivity) significantly influences the approximation ratio.
- Both on simulation and on real quantum hardware, all variants demonstrate superior results when applied to complete and regular graphs, rather than random graphs.



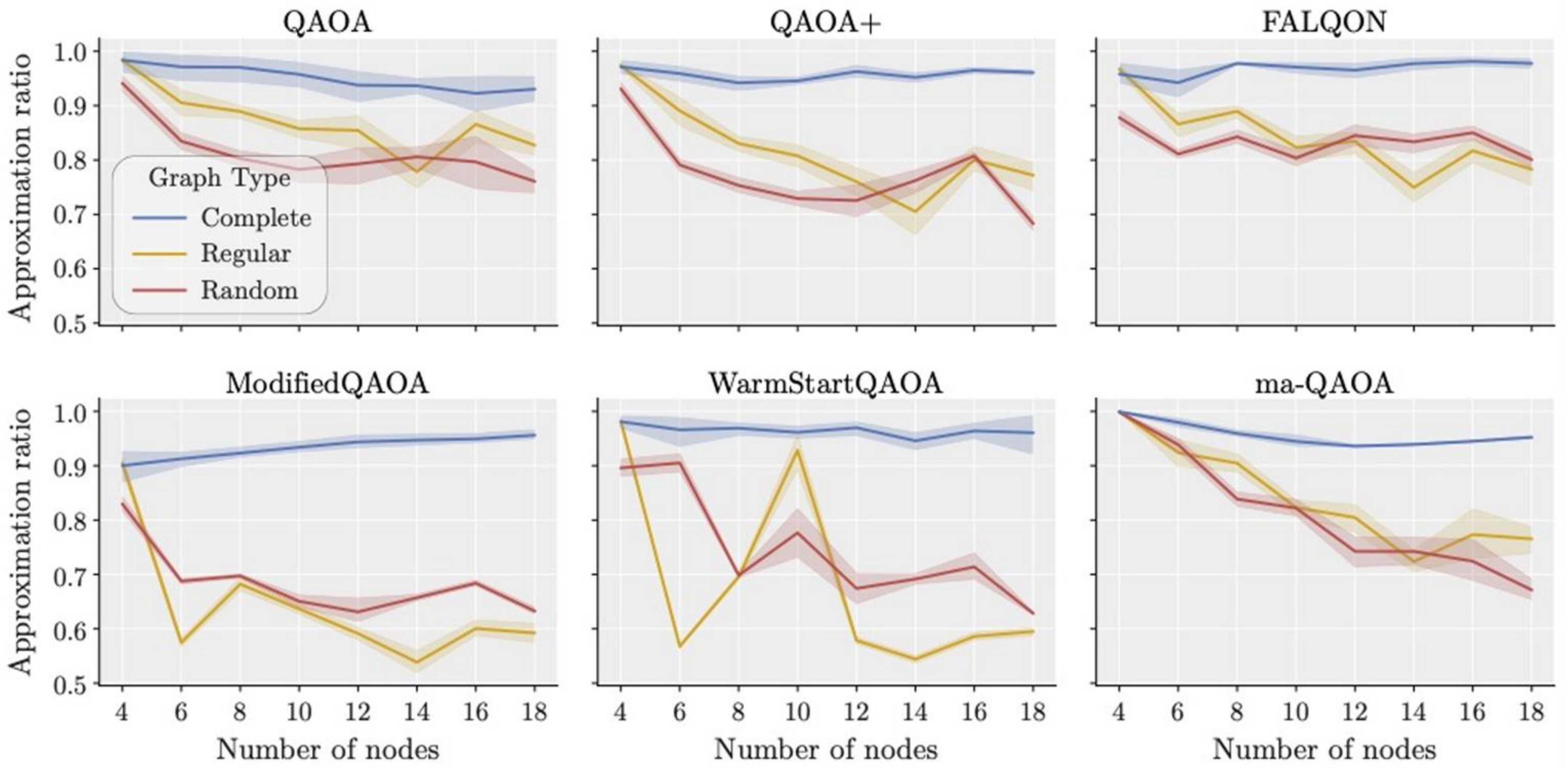
Problem size vs resource usage

- Unique trade-offs between approximation capabilities and amount of computational resources.
- Some variants achieve higher approximation ratios but require more gates, have higher circuit depth, or need more circuit evaluations, resulting in increased computation time.

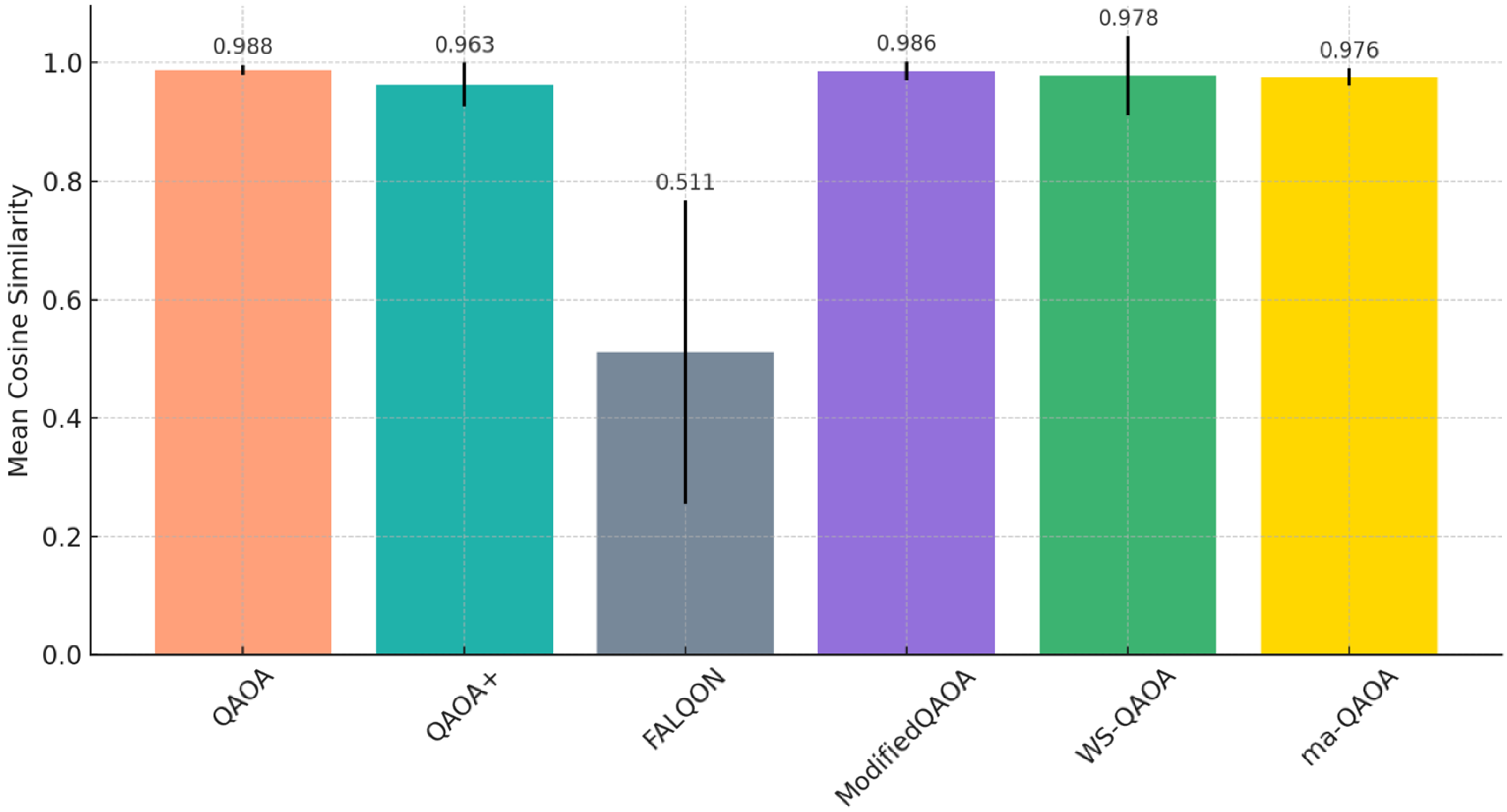


Problem size vs approximation ratio

- Declining trend of mean approximation ratios with increasing graph size.
- A strong dependence on graph type is again evident.



Proximity of optimal parameters to initial random guess



Our key takeaways

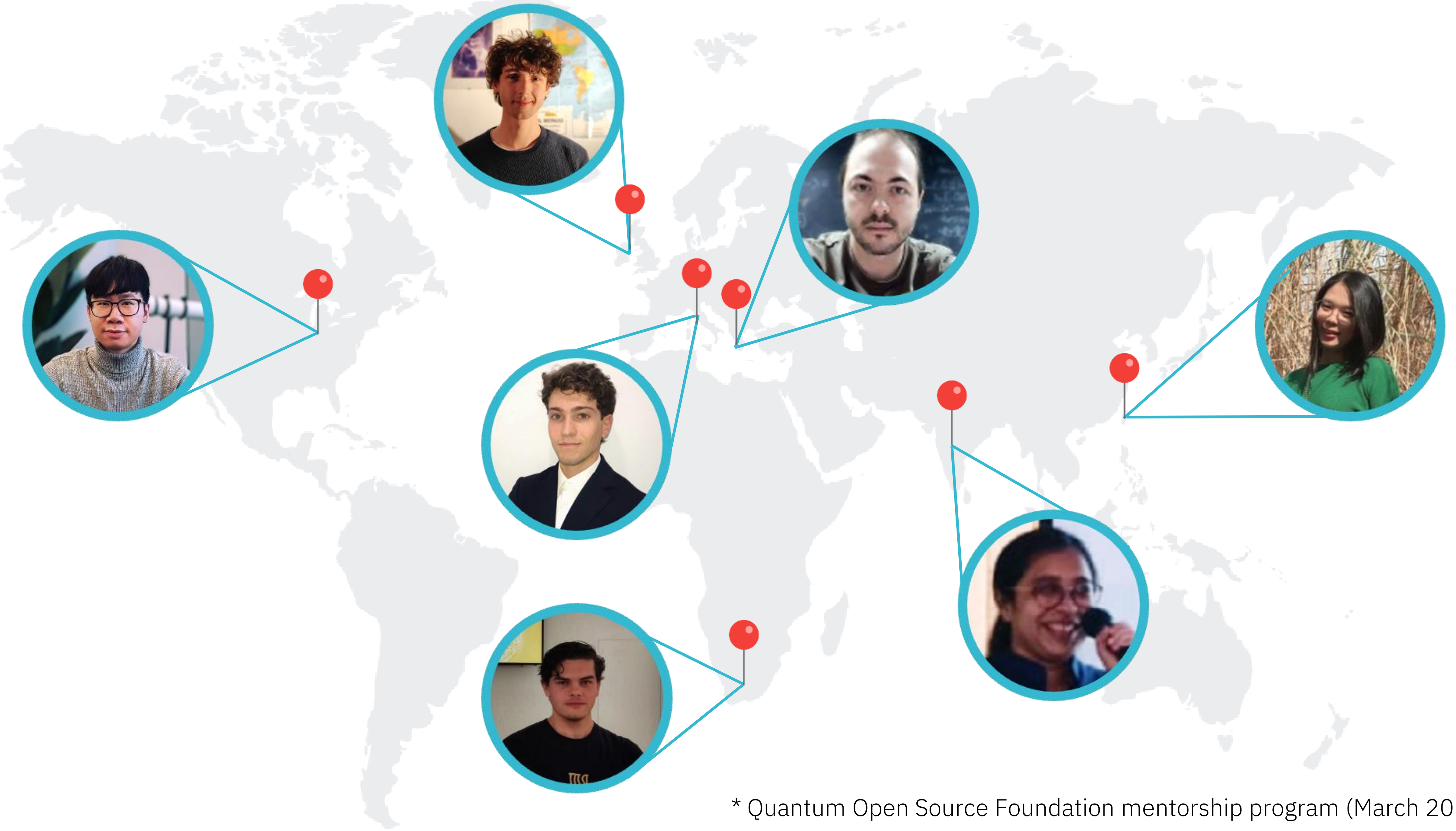
- There is no one “QAOA”; variants show significantly different characteristics.

- QAOA performance is very problem-dependent: ansatz-problem dependency investigation is very high priority.

- To understand QAOA better:
    - apply to diverse set of problems and track efficiency and performance;
    - investigate parameter space characteristics.

Team*

(Lots of Zoom meetings)



* Quantum Open Source Foundation mentorship program (March 2022)

Work in progress

A Review on Quantum Approximate Optimization Algorithm and its Variants

Kostas Blekos*[1], Dean Brand[2], Andrea Ceschini[3], Chiao-Hui Chou[4], Rui-Hao Li[5], Komal Pandya[6], and Alessandro Summer[7]

Work in progress to extend the framework:

- Release as Open Source
- **Public database** of results; user updatable
- Include *many* more problems (max-cut graphs)
- Include other models (TSP, SK, ...)