

Predict and Conquer: Navigating Algorithm Trade-offs with Quantum Design Automation

Simon Thelen^{1,2} and Wolfgang Mauerer^{1,3}

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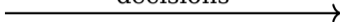
Application requirements

- ▶ Solution quality
- ▶ Runtime
- ▶ # Qubits
- ▶ Noise resistance
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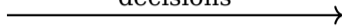
decisions



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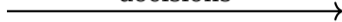
Quantum algorithms

Example use case: combinatorial optimisation

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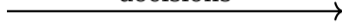
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Quantum algorithms

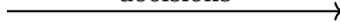
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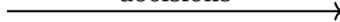
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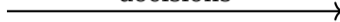
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 - ▶ Problem formulation
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Example use case: combinatorial optimisation

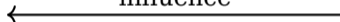
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influence



Quantum algorithms

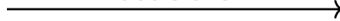
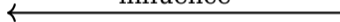
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**predict
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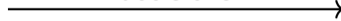
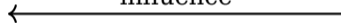
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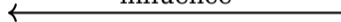
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automate
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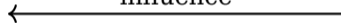
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⇒ Software framework

Simulations



Ideal



Noisy

Simulations



Ideal



Noisy

Metrics

Solution quality $\in [0, 1]$ 

Runtime in seconds

Simulations



Ideal



Noisy

Metrics

Solution quality $\in [0, 1]$ 

Runtime in seconds

Optimisation problems (#qubits $\in \{5, 6, \dots, 19\}$)

Max-cut

4	9	3	6	8
2	1	8	5	9
Sum:	Sum:			
27	28			

Partition



Minimum vertex cover



Maximum independent set

$$(A \vee \neg B \vee C) \wedge$$

$$(\neg A \vee B \vee \neg C)$$

Max-3SAT

Simulations



Ideal



Noisy

Metrics



Solution quality $\in [0, 1]$



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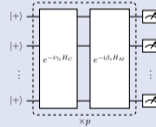


Maximum independent set

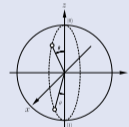
$$(A \vee \neg B \vee C) \wedge (\neg A \vee B \vee \neg C)$$

Max-3SAT

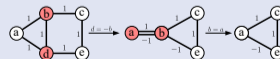
Algorithms (#layers $\in \{1, 2, \dots, 7\}$)



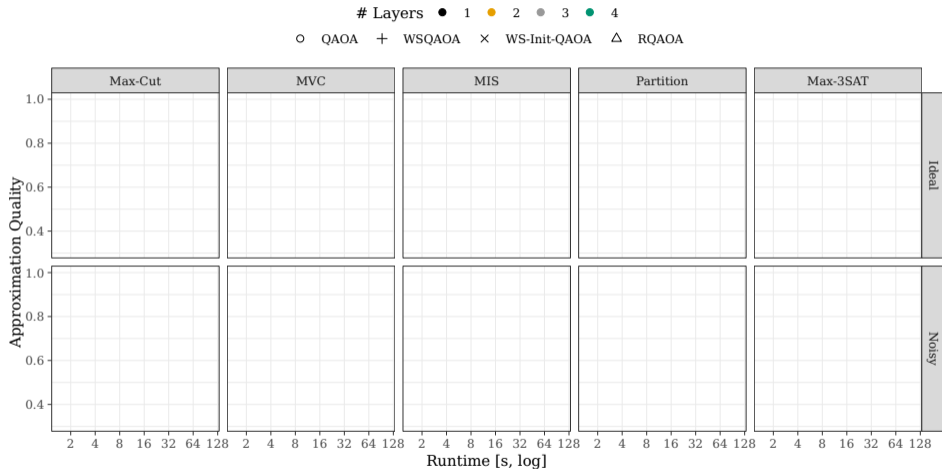
QAOA

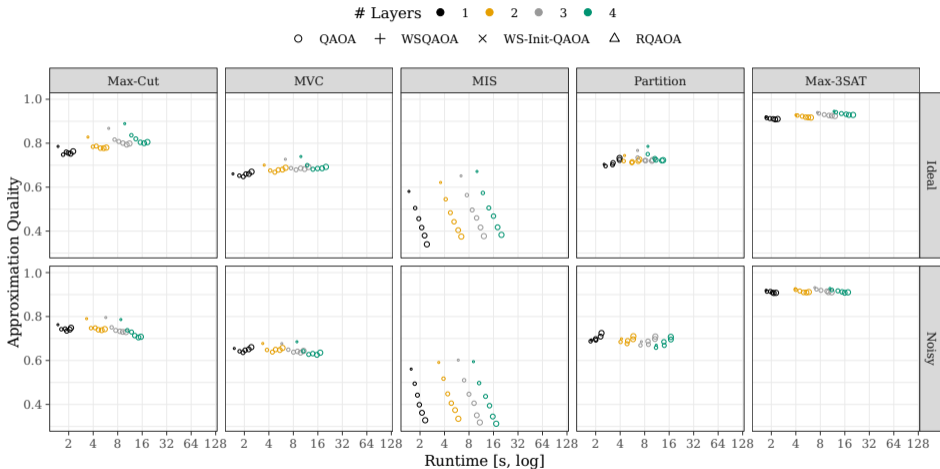


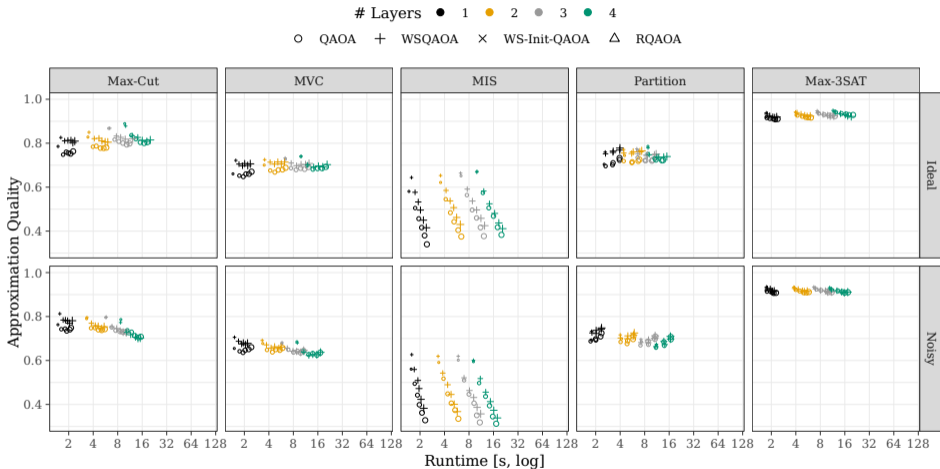
WSQAOA/WS-Init-QAOA

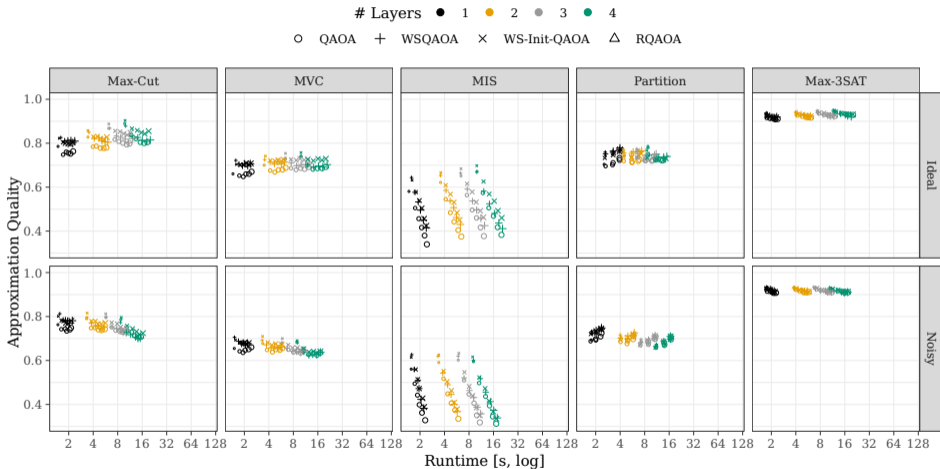


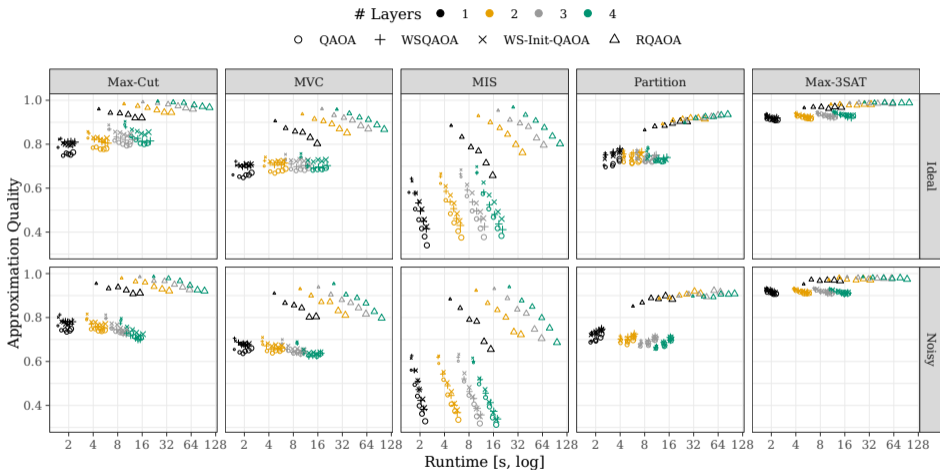
Recursive QAOA











Predict algorithm *runtime* and *solution quality* accurately
for *diverse quantum hardware*, using *few, small-scale*
baseline instances.

For each problem, find bounds: $LB(x) \leq f(x) \leq UB(x)$

$$\text{Normalize: } Y = \frac{f(x) - LB(x)}{UB(x) - LB(x)}$$

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Beta Regression

$$Y \approx \frac{1}{1 + e^{-(\alpha + \beta n + \gamma d)}}$$

n : qubit count, d : layer count, b : baseline size

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Power Law Decay

$$Y \approx \bar{Y}_d^{(b)} (1 + \alpha(n - b))^\beta$$

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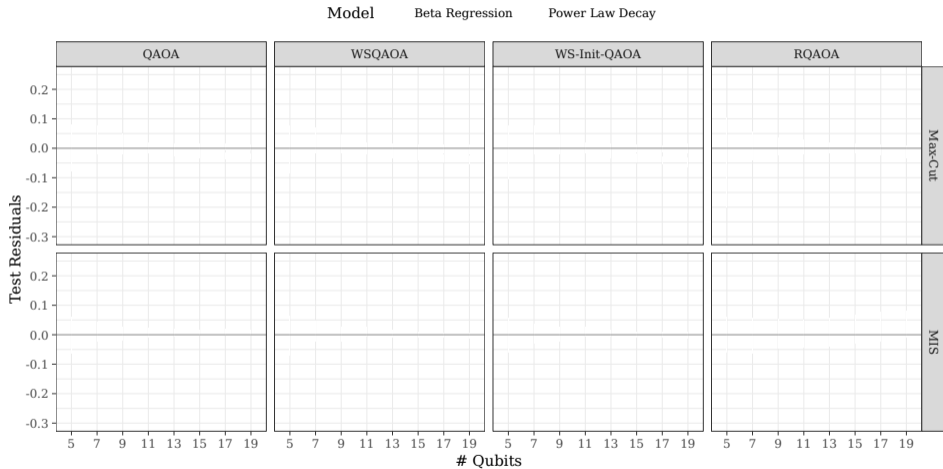
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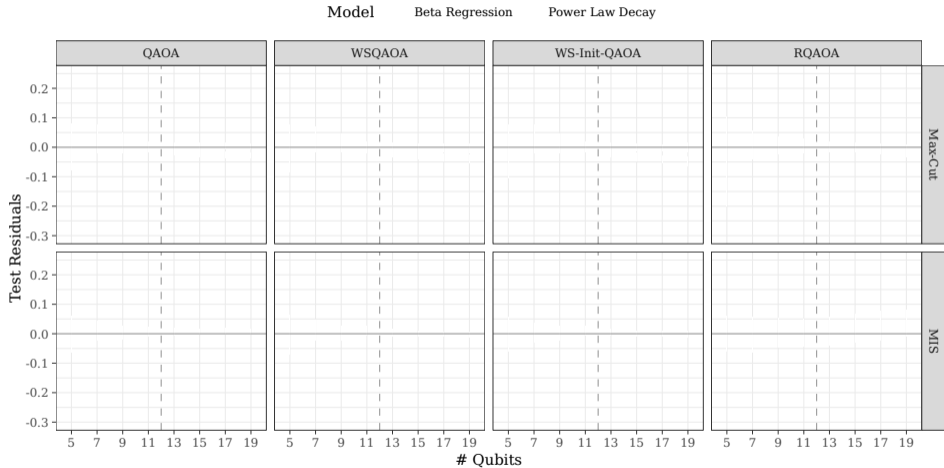
Noisy Quality Degradation

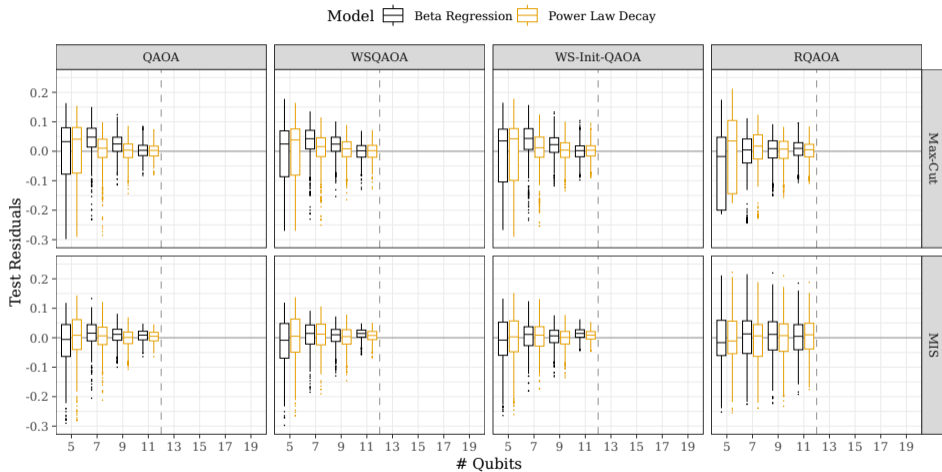
$$\begin{aligned} f_{\text{noisy}}(x) &\approx \text{LB}(x) \\ &+ (f_{\text{ideal}} - \text{LB}(x)) \\ &\cdot (1 - l\beta)^{nd_{\text{c}} - x} \\ &\cdot (1 - l\gamma)^{n_{\text{c}} - x} \end{aligned}$$

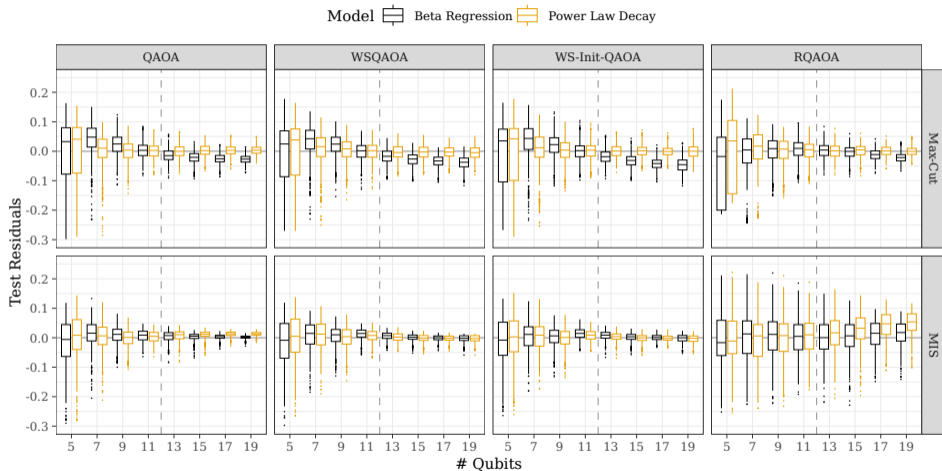
cf. Marshall et al. 2020, Xue et al. 2021

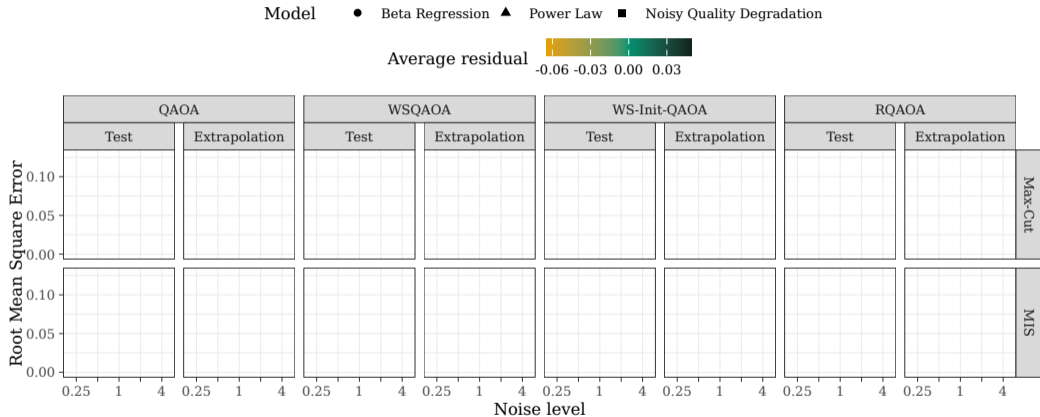
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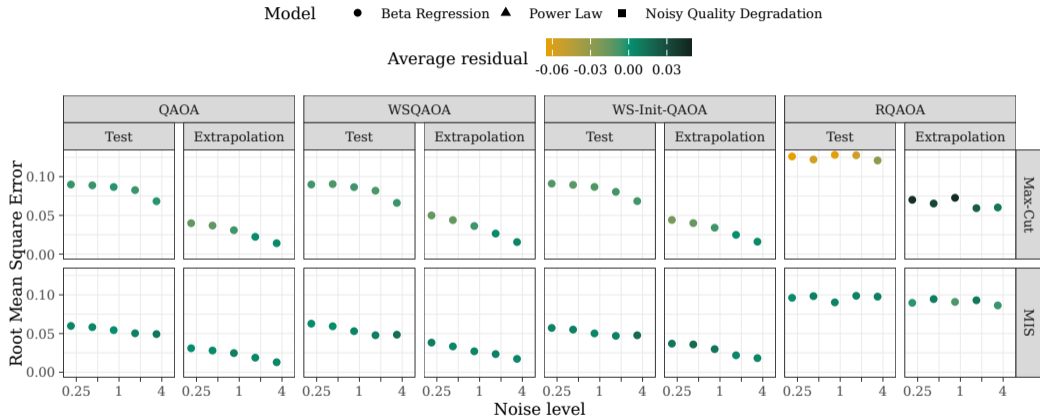




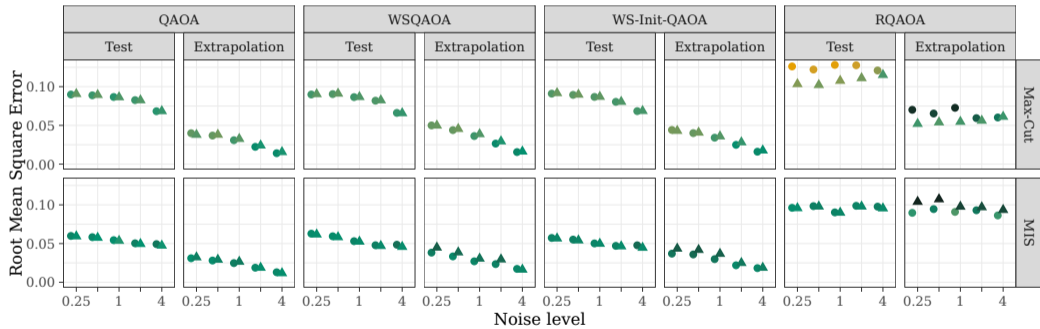






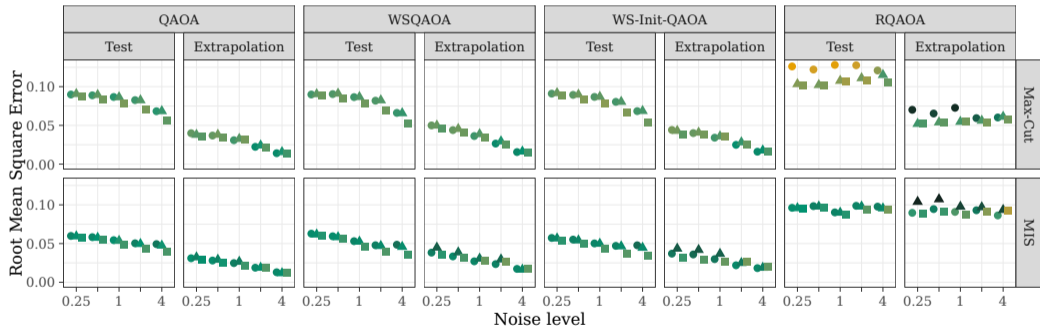


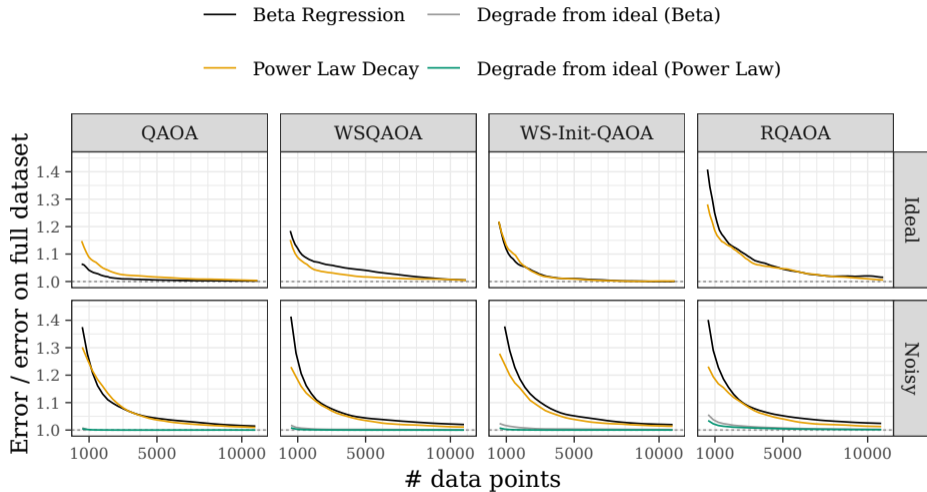
Model ● Beta Regression ▲ Power Law ■ Noisy Quality Degradation

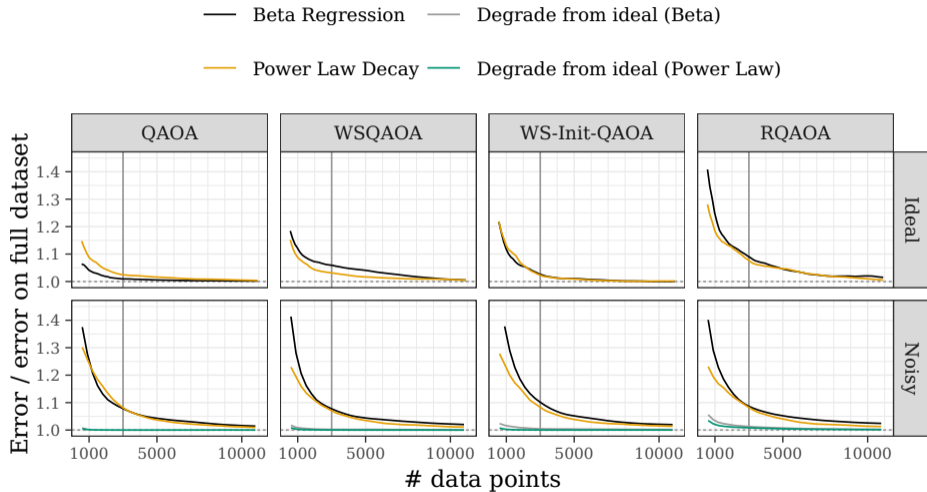


Model ● Beta Regression ▲ Power Law ■ Noisy Quality Degradation

Average residual  -0.06 -0.03 0.00 0.03







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Software framework

`github.com/lfd/qce2025-design-automation`

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from quantum_framework import *  
import networkx as nx  
  
framework = AlgorithmSelectionFramework()  
framework.add_results(load_results())
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from quantum_framework import *  
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with RELATIVE_SOLUTION_QUALITY >= 0.75:
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with RELATIVE_SOLUTION_QUALITY >= 0.75:
    with minimize(RUNTIME):
```

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framework = AlgorithmSelectionFramework()
framework.add_results(load_results())
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with RELATIVE_SOLUTION_QUALITY >= 0.75:
    with minimize(RUNTIME):
        result = framework.quantum_solve(instance)
```

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from quantum_framework import *
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framework = AlgorithmSelectionFramework()
framework.add_results(load_results())
instance = MaxCut(nx.erdos_renyi_graph(n = 30, p = 0.5))

with RELATIVE_SOLUTION_QUALITY >= 0.75:
    with minimize(RUNTIME):
        result = framework.quantum_solve(instance)

with maximize(SOLUTION_QUALITY), (
    (RUNTIME <= 10 * SECONDS) &
    (SOLUTION_QUALITY_PER_RUNTIME >= 100)
):
    result = framework.quantum_solve(instance)
```

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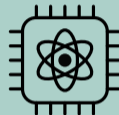
with maximize(2/3 * SOLUTION_QUALITY - 1/3 * RUNTIME):
    result = framework.quantum_solve(instance)
```

User Code

```
with optimize(2/3 * RUNTIME + 1/3 * SOLUTION_QUALITY):  
    with (  
        RUNTIME ≤ 100 * MILLI_SECONDS &  
        RELATIVE_SOLUTION_QUALITY ≥ 0.8  
    ):  
        solution = framework.quantum_solve(problem)
```

Algorithm Selection Framework

Quantum System



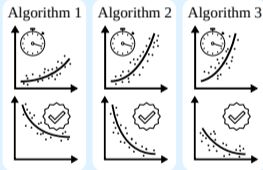
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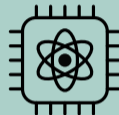


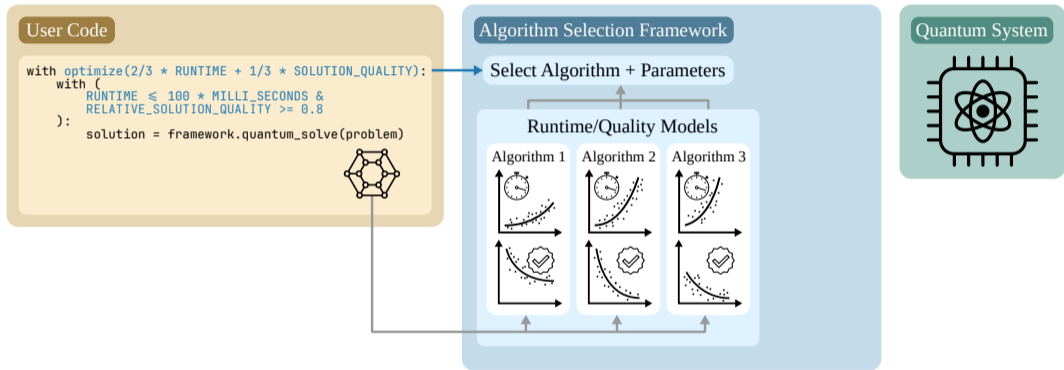
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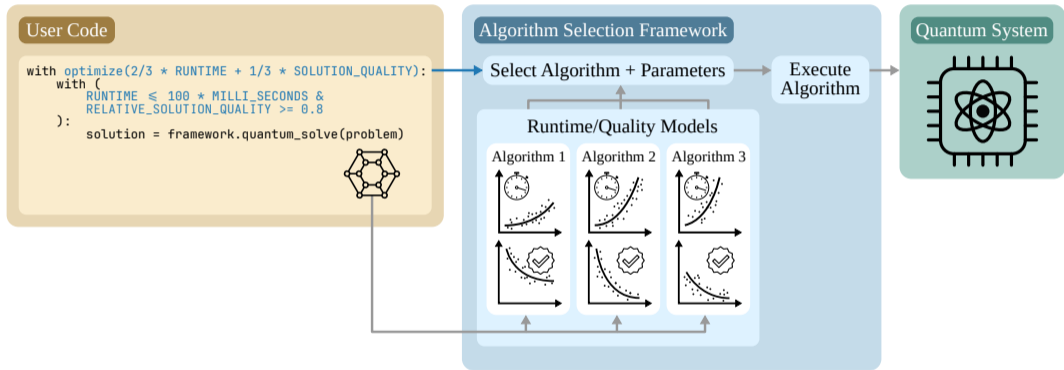
Runtime/Quality Models

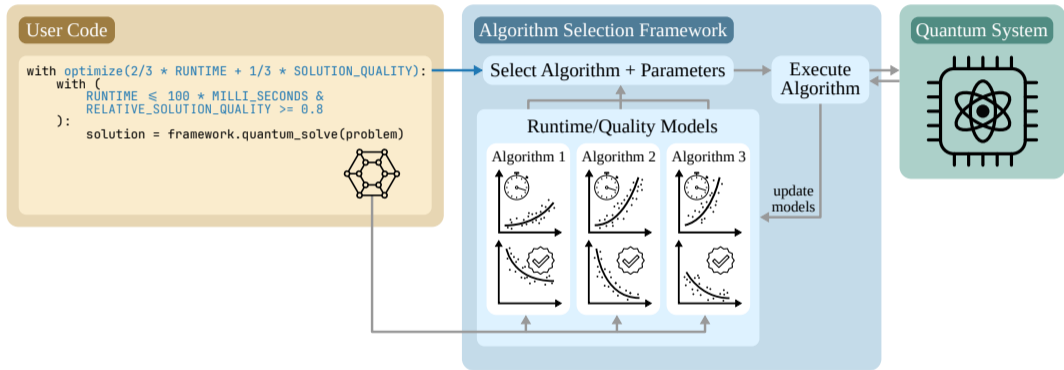


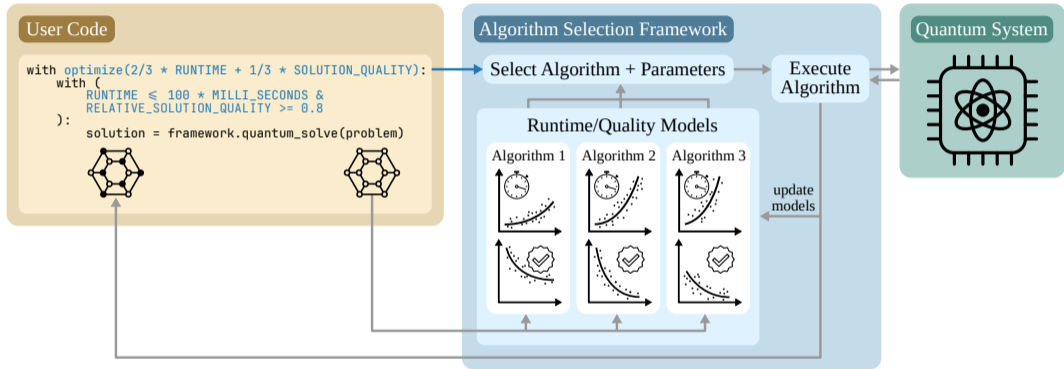
Quantum System











Requirements

- ▶ Runtime
- ▶ Simulation error
- ▶ Quantum resources

Design decisions

- ▶ Approach
(Trotter-Suzuki, Analog, Quantum Walk)
- ▶ Parameters
(layer count, gate-based/analog hybrid)

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```
with maximize(INV_SIMULATION_ERROR_PER_RUNTIME), (  
    SIMULATION_ERROR <= 0.001  
):  
    hamiltonian = Hamiltonian(...)  
    result = framework.evolve_hamiltonian(  
        hamiltonian,  
        psi_0 = "0" * n, observable="Z" * n,  
    )
```

- ▶ Other problem classes
- ▶ Other influence factors
 - ▶ Number of measurements
 - ▶ Optimizer specification
 - ▶ ...
- ▶ Framework improvements

Experimental setup

Simulations

Ideal Noisy

Optimisation problems (#qubits ∈ {5, 6, ..., 19})

Max-cut Partition Minimum vertex cover

Maximum independent set Max-3SAT

Metrics

Solution quality ∈ [0, 1] Runtime in seconds

Algorithms (#layers ∈ {1, 2, ..., 7})

QADA WSGQA/WS-In-QADA

Recursive QADA

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Experiment results

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Model performance (noisy)

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Framework architecture

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Backup Slides

Runtime model

$$T(x) \approx \alpha d_{C-X}^{\beta}$$

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