

# **Quantum Circuit Transformation using Reinforcement Learning**

## ABSTRACT

Quantum computer in the NISQ era (Noisy Intermediate Scale Quantum) suffer from limited qubit connectivity for two qubit operations (only physically adjacent qubits can interact) and high error rates, which compound when increasing the depth of the circuit, making execution of deep quantum circuits an unfeasible task.

To make an arbitrary quantum circuit executable on a given target architecture, a quantum compiler has to insert SWAP gates so that gates in the original circuit only ever occur between qubits located at adjacent nodes, a process known as *Qubit Routing*<sup>1</sup>. The process produce a new circuit, possibly with a greater depth, that implements the same unitary function as the original circuit while respecting the topological constraints

## **OBJECTIVE**

Classical Greedy routing approaches are currently in use, while a couple of combinatorial RL approaches are also used, which learn the value function and attempt to perform simulated annealing runs on them. We aim to improve the speed and efficiency (depth overhead) of these methods by using RL in an autoregressive setting.

## METHOD

We use Policy Gradient methods in reinforcement learning and tree searches through them to find efficient methods of quantum compilation. It's easier to attempt to learn the policy directly than a value function.

The Combinatorial function is achieved using an autoregressive setting, where each action (for each qubit) in each step is dependent on the operations in the previous step.



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Fig. 1 An example of qubit routing. *Our framework will incorporate a* strategy to perform qubit routing -(1) Qubit Movement, and (2) Qubit Allocation, such that the final transformed circuit (i.e., the one mapped to the topology) has the lowest depth (or size).

## **RL FORMULATION AND RESULTS**

 $V(s) = \max_{a'} Q(s, a)$ 

Circuit

rd84\_142

adr4\_197

radd\_250

sm66\_145

misex1\_241

cycle10\_2\_110

square\_root\_7

rd73\_252

sqn\_258

z4 268

$$Q(s,a) = \sum_{s'} R(s,a,s') + \gamma V(s')$$
$$UCT_s(a) = Q(s,a) + \sqrt{\frac{n(s,a)}{1+n(a)}} \times p(s,a)$$

Gate Count

154

1498

1405

1343

1701

2100

2319

2648

3089

4459

2-0	5-0	9-
1-0	7-0	10-
4-0	6-0	11-
3-0	8-1	12-

Fig. 2 A snapshot of the *qubit grid* computation by the RL-based framework.



machine, each edge represents a possible 2-qubit operation.

Table 1 Results of the circuit transformation - depth and size, by our RL-based framework.

#### **References:**

On the qubit routing problem, Alexander Cowtan et al., arXiv:1902.08091

MCTS Depth

154

2016

1864

1833

2357

2883

3143

3595

3967

6067

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