
ACM SAC '26 – Quantum Software Engineering Practices (QSE) Track

Variational Quantum Rainbow Deep Q-Network for Optimizing Resource Allocation Problem

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Motivation

Real-World Resource Allocation in Complex Operations

Many real-world systems must **assign multiple tasks to different roles simultaneously**:

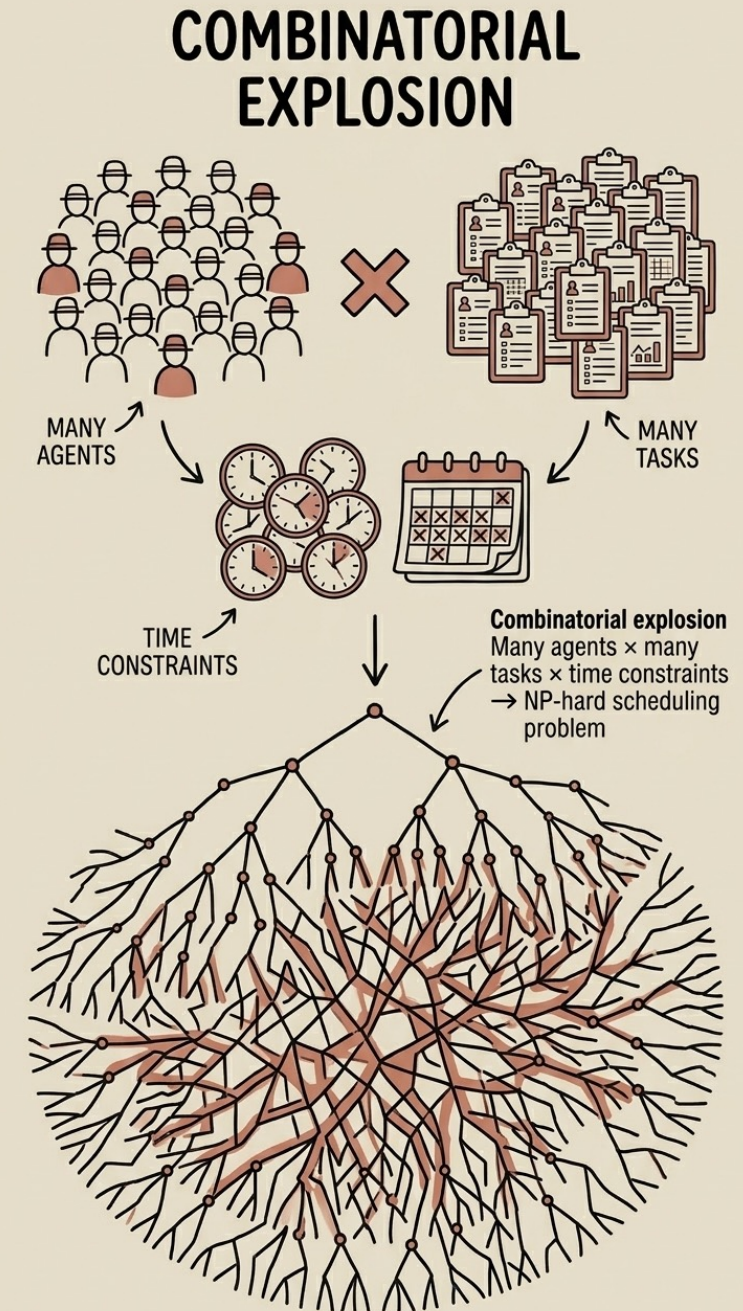
- Healthcare emergency response
- Wildfire disaster management
- Police and public safety operations



Combinatorial Explosion

Many agents × many tasks ×
time constraints

→ NP-hard scheduling problem

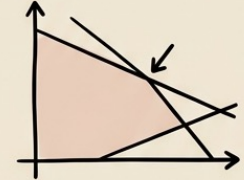


Traditional Optimization Approaches

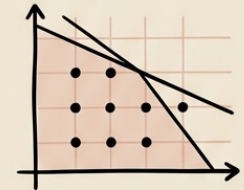
- Linear Programming
- Mixed-Integer Programming
- Branch-and-Bound
- Metaheuristics (Genetic Algorithm, Particle Swarm Optimization, Simulated Annealing)

COMMON CLASSICAL APPROACHES

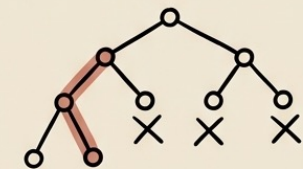
LINEAR PROGRAMMING



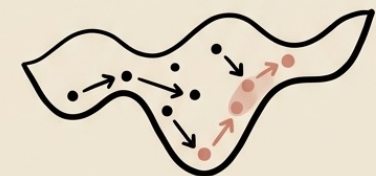
MIXED-INTEGER PROGRAMMING



BRANCH-AND-BOUND



METAHEURISTICS
(GA, PSO, SA)



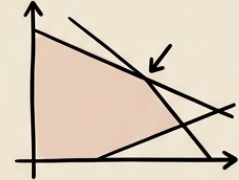
Traditional Optimization Approaches

Limitations:

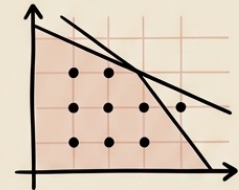
- Poor **scalability**
- High computational **cost**
- **Static environment** modelling assumptions
- Requires **hand-crafted constraints** and parameter tuning

COMMON CLASSICAL APPROACHES

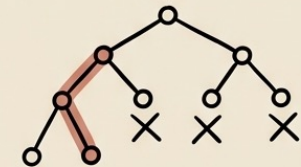
LINEAR PROGRAMMING



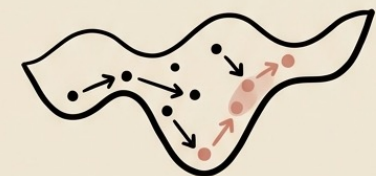
MIXED-INTEGER PROGRAMMING



BRANCH-AND-BOUND

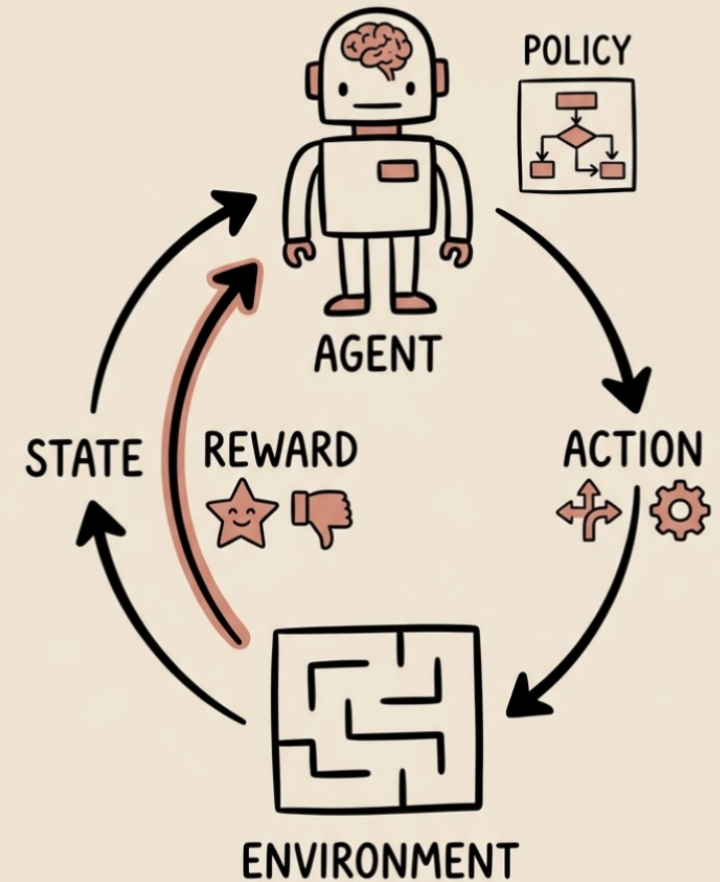


METAHEURISTICS (GA, PSO, SA)



Why Reinforcement Learning

- Learning good decisions through interaction
- Agent learns a scheduling policy
- Used in many complex decision problems

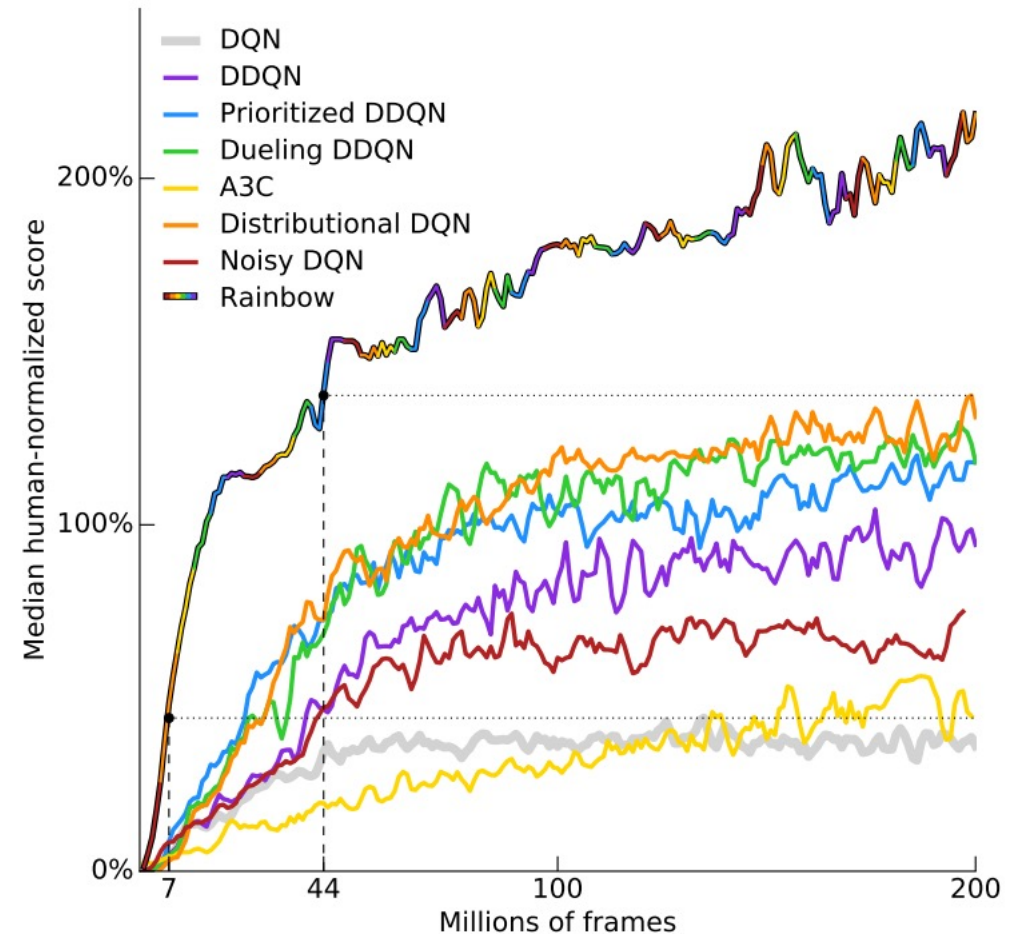


Rainbow DQN

One of the strongest DQN variants

Combines multiple RL improvements:

- Double Q-learning
- Prioritized replay
- Distributional RL
- Noisy exploration



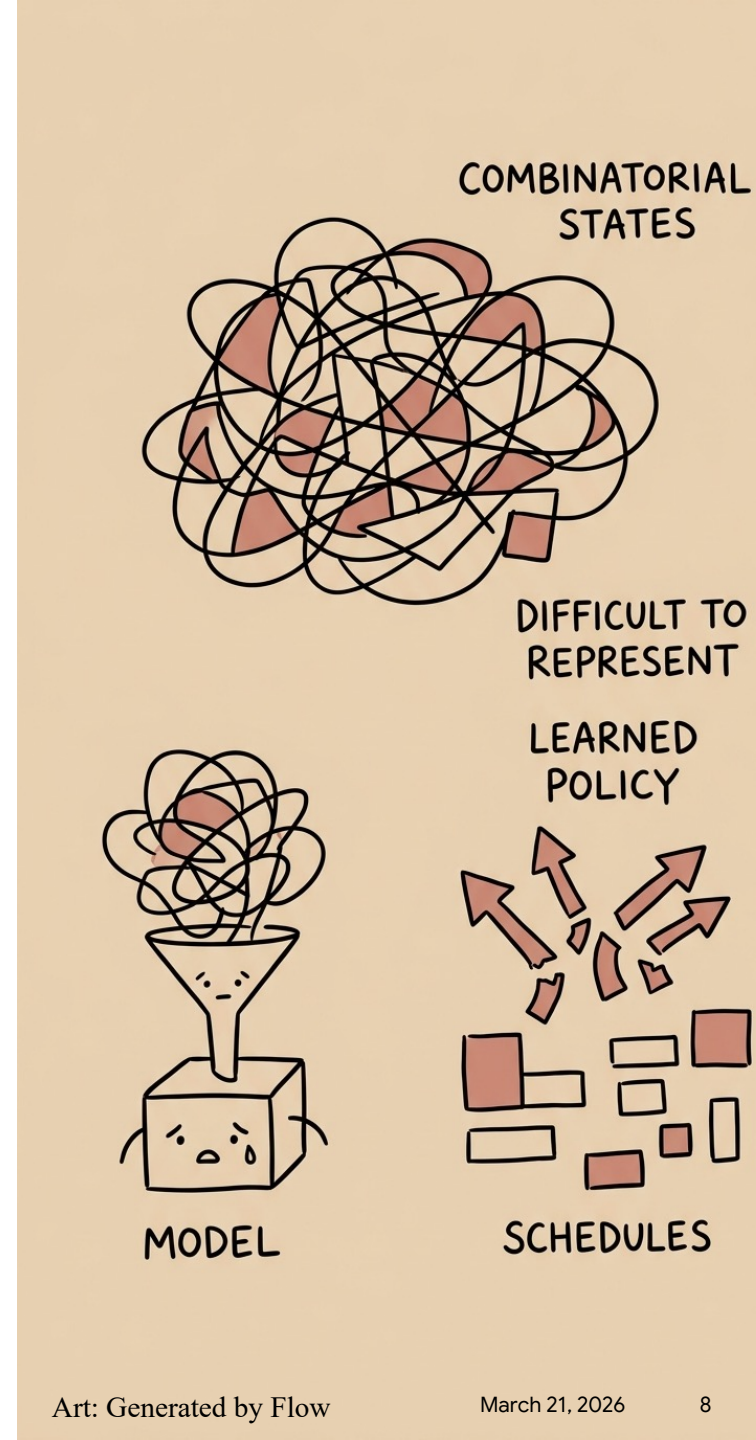
Representation Limit of Classical Deep RL Models

Deep RL models rely on neural networks to approximate value functions.

Key issue: **representation capacity**.

- Complex combinatorial states are difficult to represent.

If the model cannot represent these relationships well, **the learned policy may not find optimal schedules.**

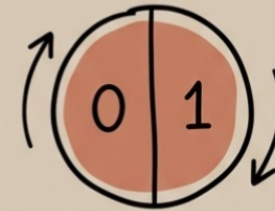


Why Quantum RL?

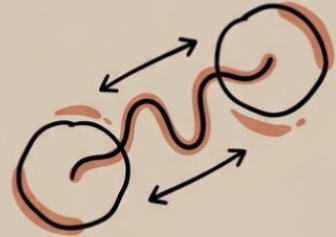
Quantum computing offers:

- Superposition
- Entanglement
- Parallel exploration of states
- High-dimensional representations

Quantum circuits can act as **feature extractors** in RL systems



SUPERPOSITION



ENTANGLEMENT



PARALLEL EXPLORATION
OF STATES



HIGH-DIMENSIONAL
REPRESENTATIONS

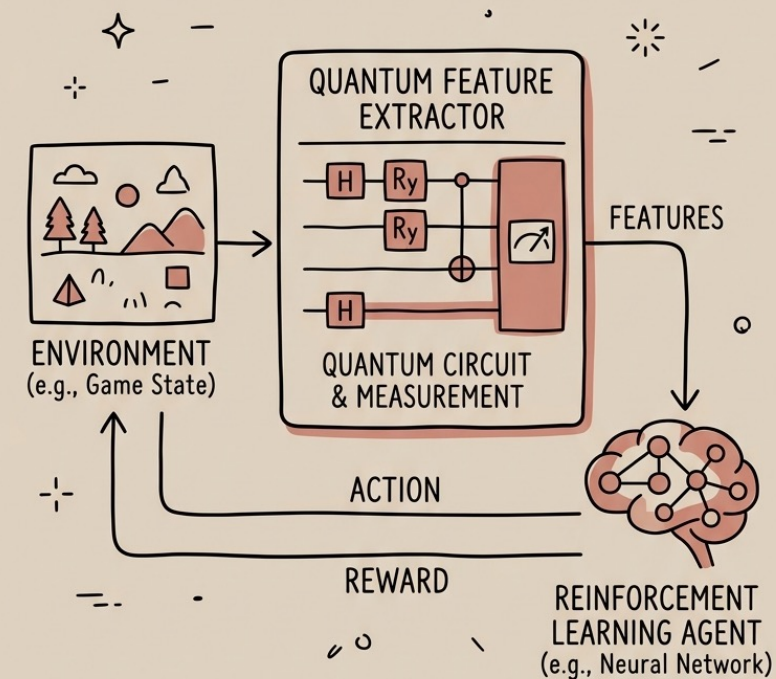
Our Proposed Solution

Variational Quantum Rainbow Deep Q-Network (VQR-DQN)

Combine RL with **quantum-enhanced feature extraction**:

- **Richer representation** of complex decision spaces
- Improved **modeling** of correlations in combinatorial problems
- Potential for **better policies**

QUANTUM CIRCUITS AS FEATURE EXTRACTORS IN RL

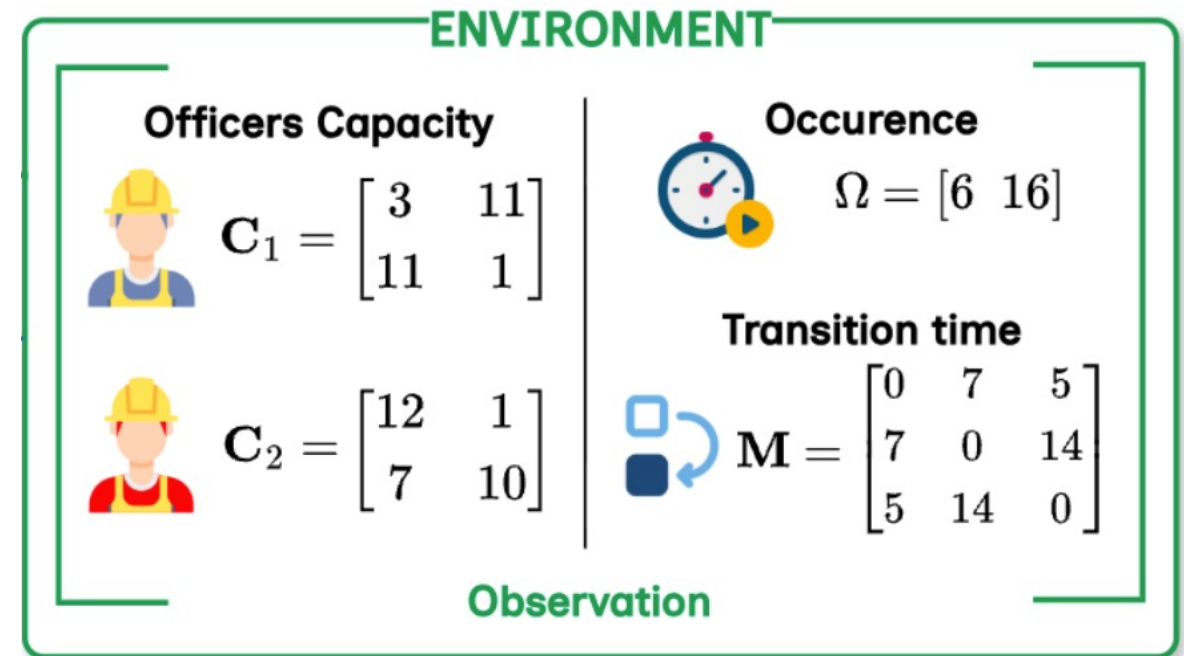


Human Resource Allocation Problem (HRAP)

Formulated as an **Markov Decision Process (MDP)**

Environment simulates:

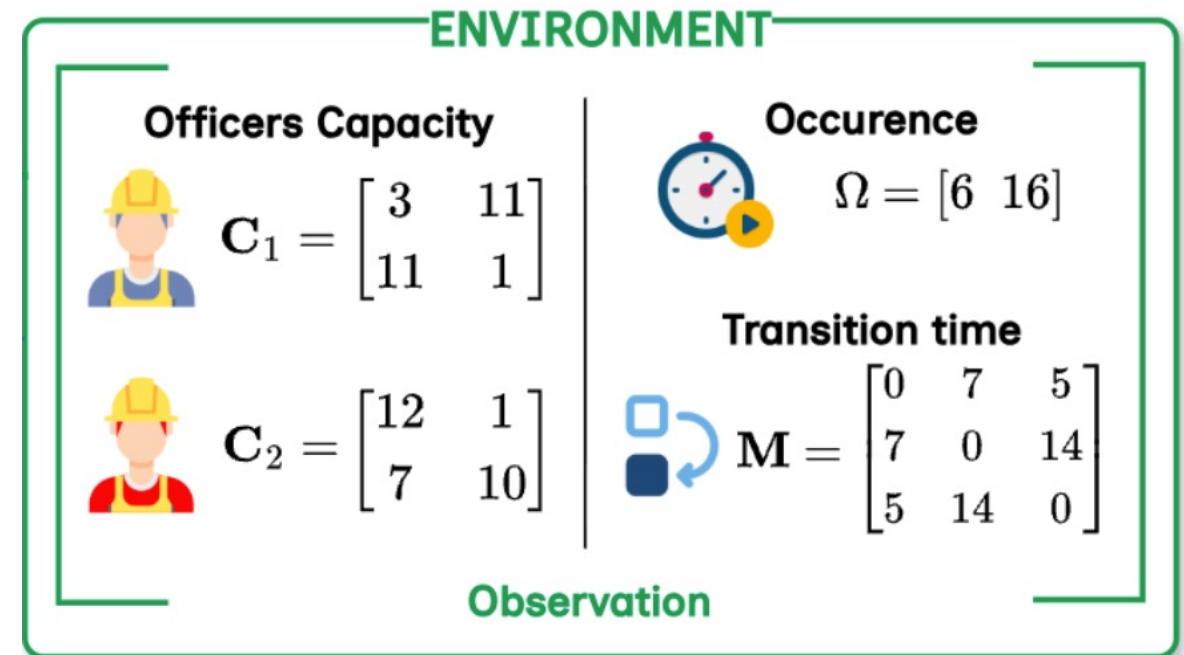
- Officers O
- Events E
- Tasks T



State Representation

State includes:

- **Officer** capability C_o
- **Event** occurrence time Ω
- **Transition** (Travel) time M



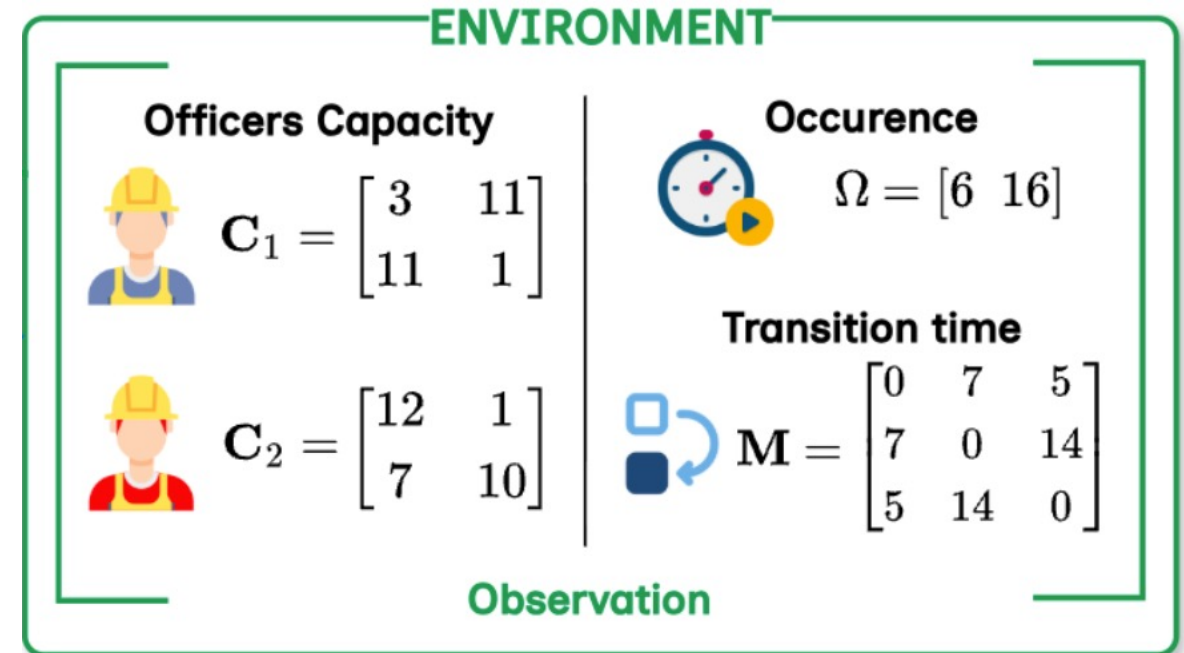
Action Space

Action:

For each task t in event e ,
assign officer \rightarrow task

Action space:

$O^{E \times T}$ grows rapidly with
problem size



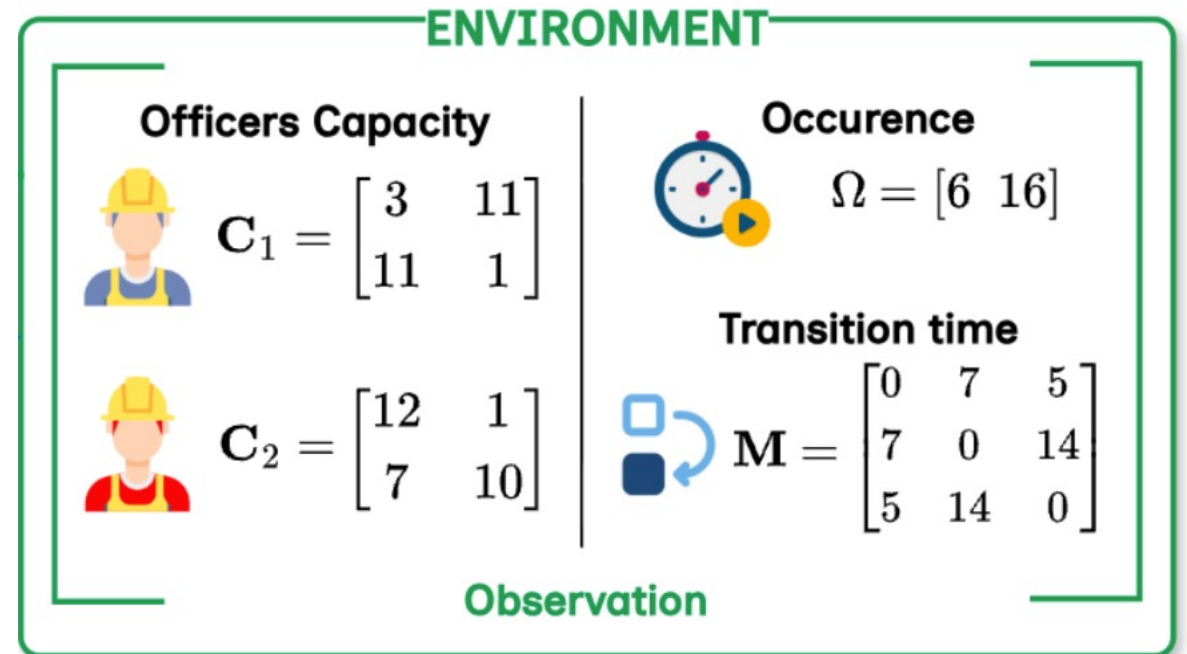
Reward Function

Reward = negative of the maximum completion time across all events

$$r_t = - \frac{\max_e (\sum_t C_{o,e,t} + \sum_{\text{transitions}} M_{e_1,e_2})}{\Psi}$$

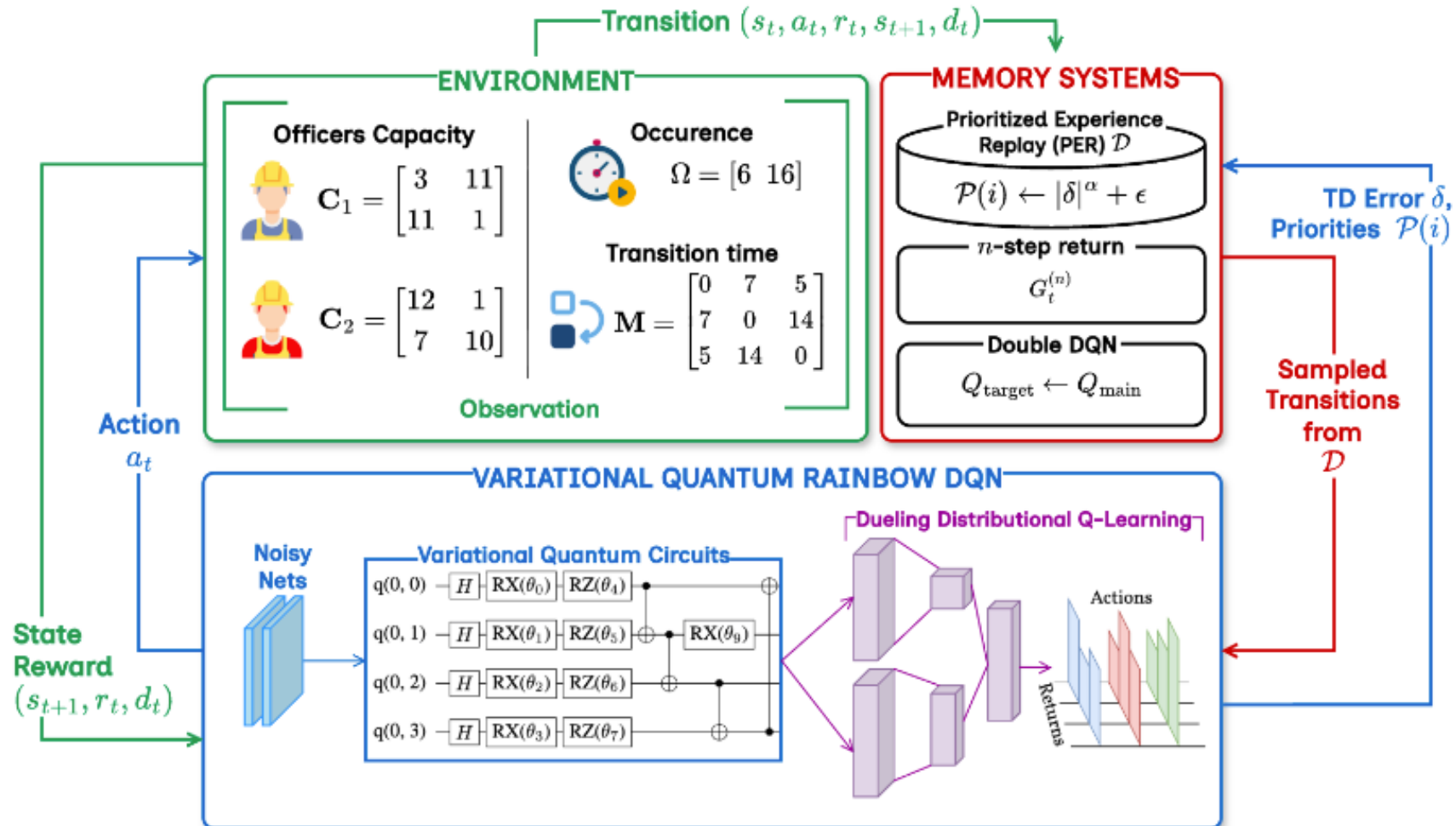
Goal:

- Minimize maximum completion time across all events.
- Prevents one event from becoming a delay bottleneck



VQR-DQN Architecture

Classical layers → Variational quantum circuit → RL decision layer

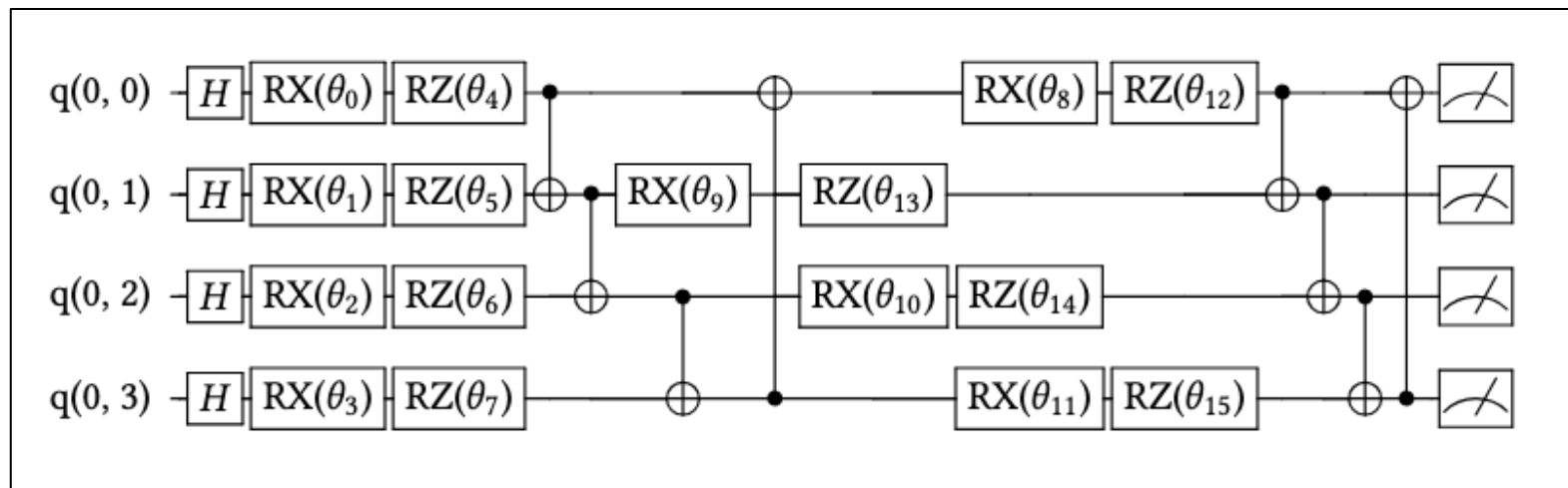


Variational Quantum Circuit

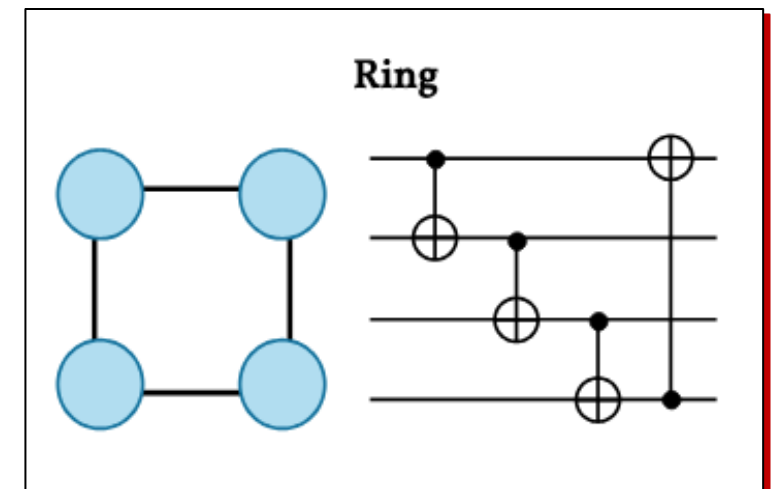
- Variational quantum circuits used as feature extractors
- CNOT gates arranged in **ring topology**

Ring topology enables:

- **Global** entanglement
- Better feature **correlations**
- Improved **expressibility**



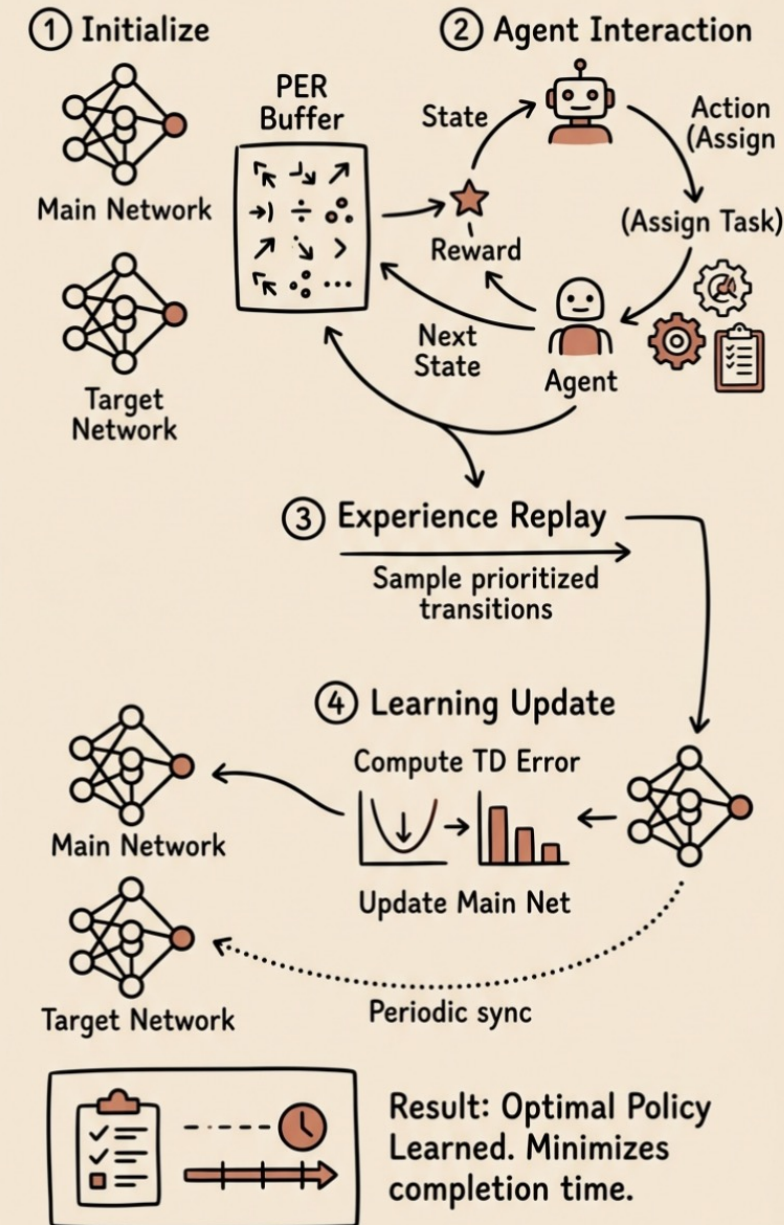
Ansatz with the Ring topology with 4 input qubits and 2 layers



Ring topology

Training Procedure

1. **Initialize:** Main & target network, PER
 2. **Agent Interaction:** State \rightarrow choose action \rightarrow receive reward & next state \rightarrow store experience
 3. **Experience Replay:** Sample PER past transitions
 4. **Learning Update:** Compute n -step return, TD error; Update network parameters
 5. **Target Network Update:** Periodically synchronize
- Result:** Learns a policy that **efficiently allocates roles to tasks and minimizes completion time.**



Experimental Setup

Simulated with TensorFlow Quantum on IonQ Aria-1

4 benchmark configurations with different officers, events, and travel times

- Training: 50,000 training episodes
- Evaluation: 200 test episodes

Methods:

- Baseline: random assignment
- Classical RL: Double DQN (DDQN), Rainbow DQN

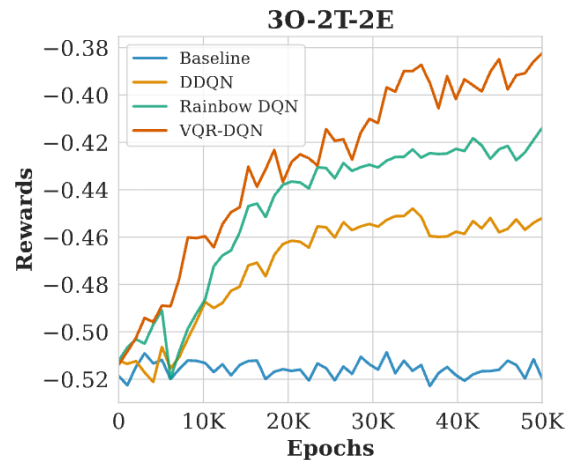


Results

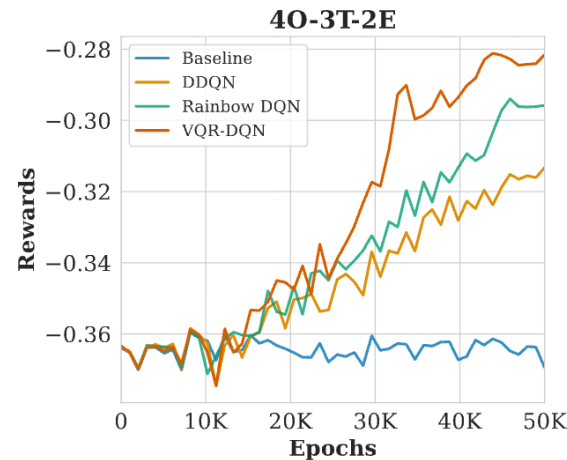
Performance improvements:

- **26.8% better** than baseline
- **4.9–13.4% better** than classical RL

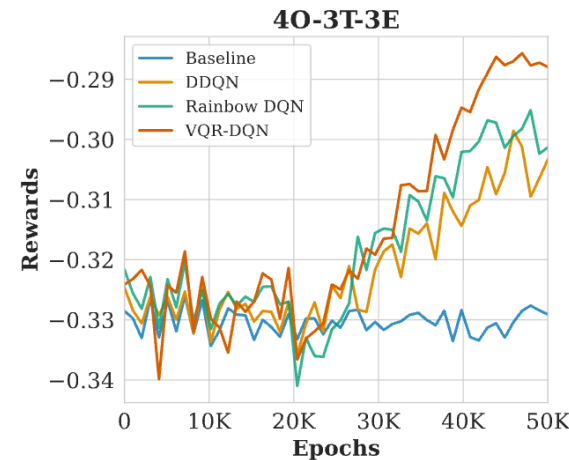
Config.	$ \mathcal{A} $	Baseline	DDQN	Rainbow DQN	VQR-DQN (Ours)
30-2T-2E	3^4	-0.5225	-0.4539 (▲ 13.1%)	-0.4189 (▲ 19.8%)	-0.3823 (▲ 26.8%)
40-3T-2E	4^6	-0.3689	-0.3132 (▲ 15.1%)	-0.2957 (▲ 19.8%)	-0.2815 (▲ 23.7%)
40-3T-3E	4^9	-0.3316	-0.3032 (▲ 8.6%)	-0.3012 (▲ 9.2%)	-0.2872 (▲ 13.4%)
50-4T-4E	5^{16}	-0.2488	-0.2366 (▲ 4.9%)	-0.2309 (▲ 7.2%)	-0.2236 (▲ 10.1%)



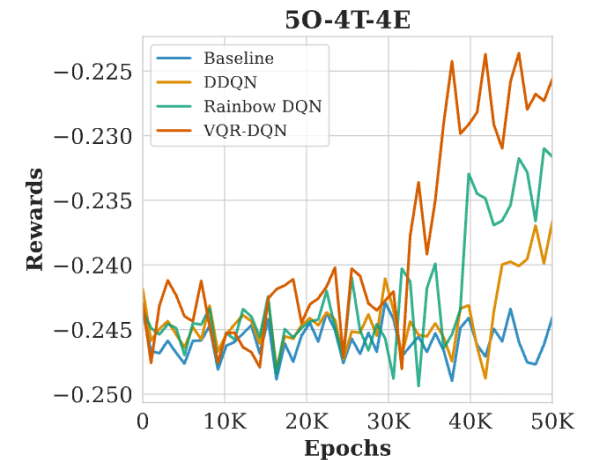
(a) $|\mathcal{A}| = 3^4$



(b) $|\mathcal{A}| = 4^6$



(c) $|\mathcal{A}| = 4^9$



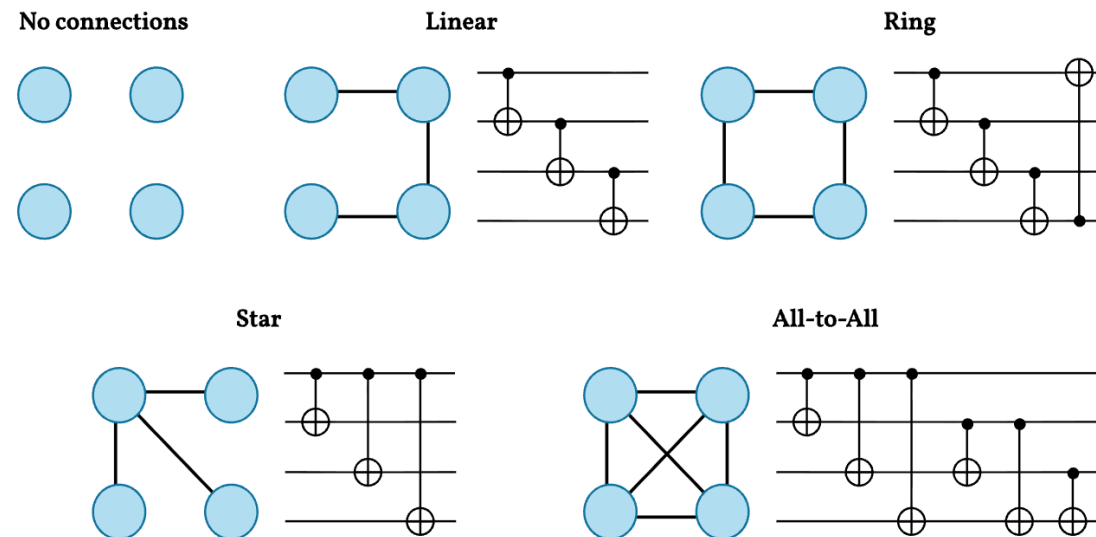
(d) $|\mathcal{A}| = 5^{16}$

Ablation Study

Impact of VQC Topologies

Ring topology achieved the best performance:

- Better **entanglement** distribution
- Higher **expressibility**
- Stronger ability to capture **complex feature** correlations



Algorithm	Rewards
Baseline	-0.5225
VQR-DQN + Linear	-0.4249 (▲ 18.7%)
VQR-DQN + Star	-0.4514 (▲ 13.6%)
VQR-DQN + Ring	-0.3823 (▲ 26.8%)
VQR-DQN + All-to-All	-0.4103 (▲ 21.5%)

Conclusion & Future Work

Our hybrid quantum-RL methods show promise for:

- Combinatorial optimization
- Resource allocation
- Complex decision systems

Next research directions:

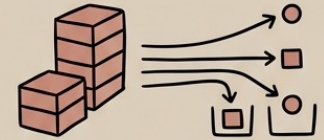
- Larger environments
- Improved quantum architectures search
- Generalized approach

Our hybrid quantum-RL methods show promise for:

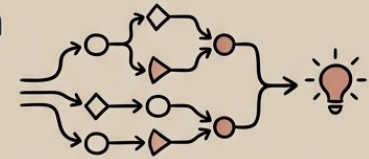
- Combinatorial optimization



- Resource allocation

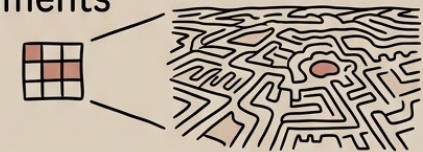


- Complex decision systems

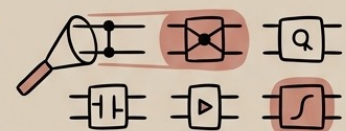


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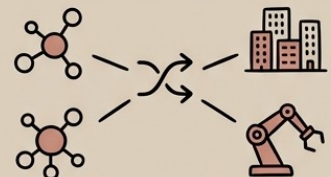
- Larger environments



- Improved quantum architectures search



- Generalized approach



Thank you!

Our mission



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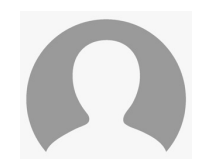
Asfia Kawnine



Atah Nuh Mih



Alireza Rahimi



Pavi P



Krishno Dey



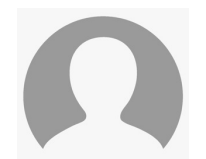
Connor McLenaghan



Ishan Randeniya



Simran Dadhich



Bohdan Savchuk

We're recruiting MSc. and PhD students!

If you are interested, contact hung.cao@unb.ca