Deep Reinforcement Learning for Quantum Network Routing

A Comparative Study on NSFNET Topology

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Outline

Introduction

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Introduction

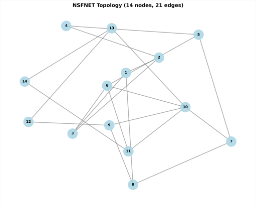
The Quantum Routing Challenge

Quantum Internet Vision

- Secure quantum key distribution
- Distributed quantum computing
- Quantum sensing networks

Unique Constraints

- Quantum decoherence
- No-cloning theorem
- Fidelity degradation



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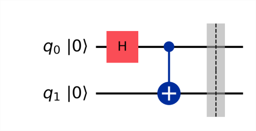

Figure 2: Bell State Generation

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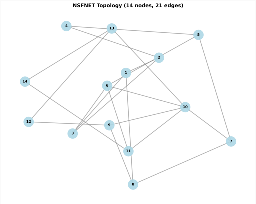

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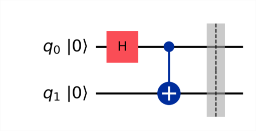

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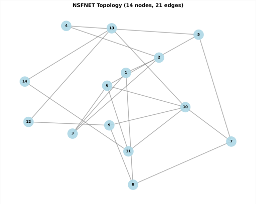

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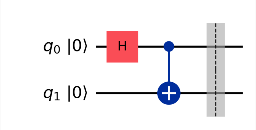

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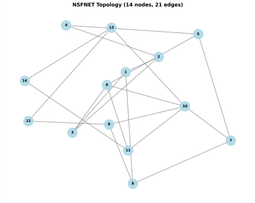

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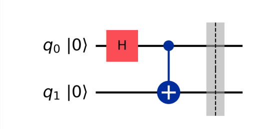

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Problem: Classical Routing Fails

Shortest Path Algorithm
Optimizes only path length:

$$\min \sum_{i \in \text{path}} 1$$

- Ignores fidelity constraints
- May traverse low-fidelity links
- Cannot adapt to dynamics

Greedy Fidelity
Maximizes immediate fidelity:

$$\max_a F(s, a)$$

Our Solution: DRL
Learns optimal policy:

$$\pi^* = \arg\max_\pi \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R_t\right]$$

- Balances multiple objectives
- Adapts to network dynamics
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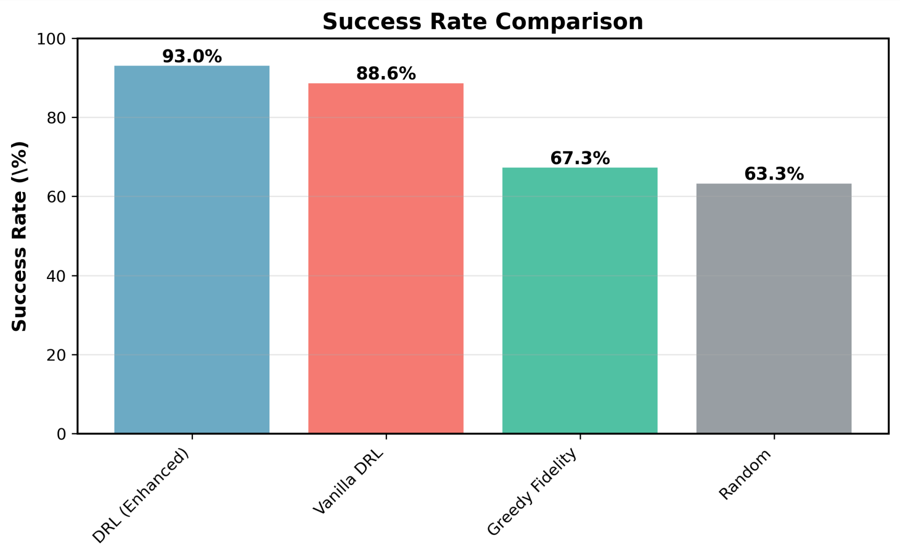
Success Rate Comparison



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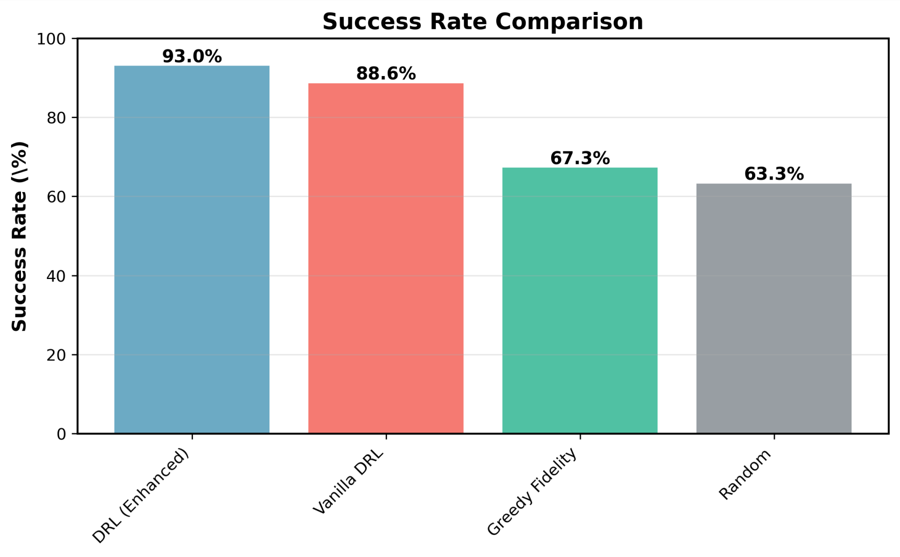
Success Rate Comparison



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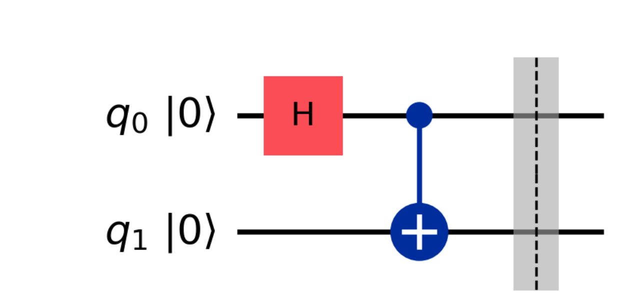
Methodology

Quantum Operations: Bell State Generation

Entanglement Creation
Creates maximally entangled Bell state:

$$|\Phi^+\rangle = \frac{|00\rangle + |11\rangle}{\sqrt{2}}$$



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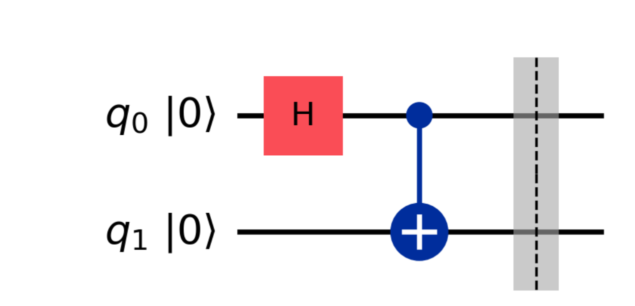

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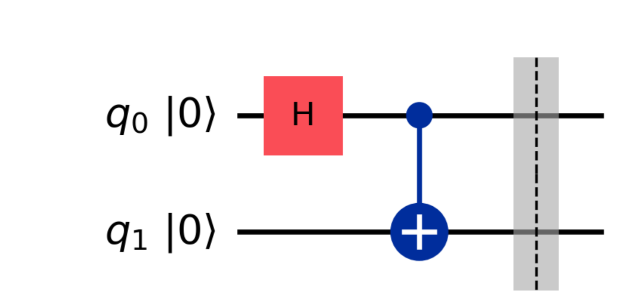
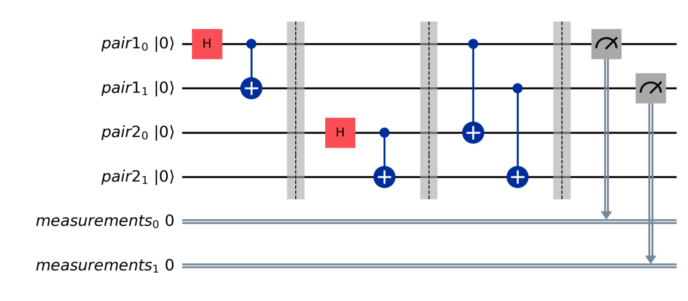


Quantum Operations: BBPSSW Purification

Fidelity Improvement

Improves entanglement fidelity by sacrificing multiple pairs:

$$F_{\text{out}} = \frac{F_{\text{in}}^2}{F_{\text{in}}^2 + (1 - F_{\text{in}})^2}$$



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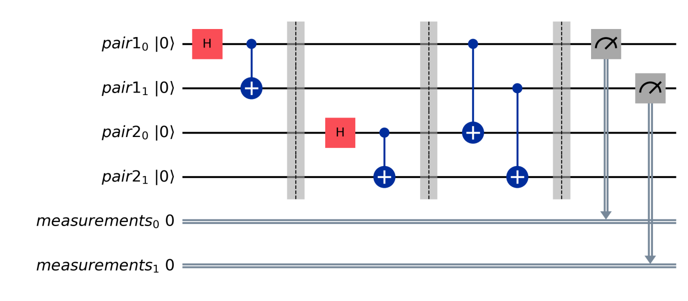

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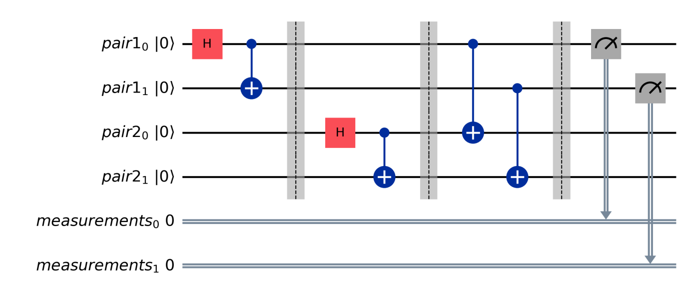

Dueling DQN Architecture

Key Innovation
Decompose Q-function:

$$Q(s,a) = V(s) + \left(A(s,a) - \frac{1}{|A|} \sum_{a'} A(s,a') \right)$$

where $V(s)$ estimates state value, $A(s,a)$ estimates advantage

Benefits

- Learn state values independently
- Better action discrimination
- Improved sample efficiency

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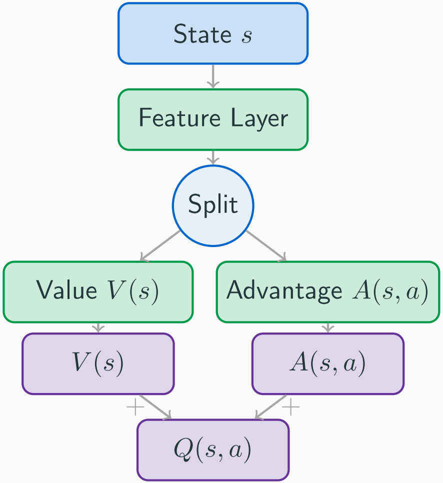

Prioritized Experience Replay

Core Idea
Sample transitions with probability:

$$P(i) = \frac{p_i^\alpha}{\sum_k p_k^\alpha}$$

where $p_i = |\delta_i| + \epsilon$ (TD-error)

Importance sampling weight:

$$w_i = \left(\frac{1}{N} \cdot \frac{1}{P(i)}\right)^\beta$$

Learn more from surprising outcomes

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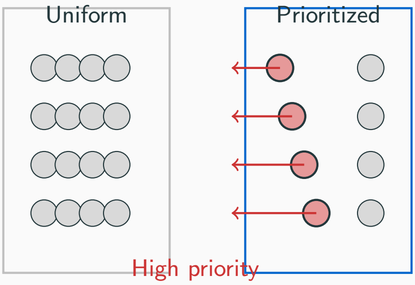

Learn more from surprising outcomes

Double DQN

Problem
Standard DQN overestimates Q-values

Solution: Decouple

- Action selection: Main network
- Value estimation: Target network

$$a^* = \arg\max_a Q(s', a; \theta)$$

$$y = r + \gamma Q(s', a^*; \theta^-)$$

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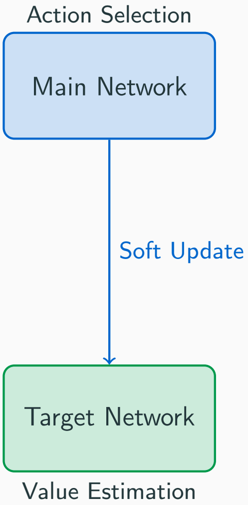

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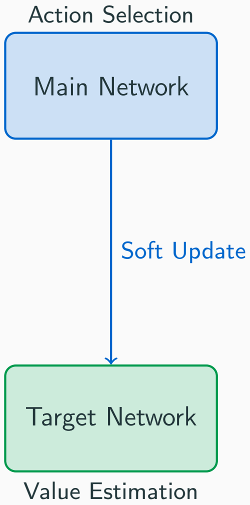

Training Configuration

Hyperparameters

Learning rate	$\alpha = 10^{-4}$
Batch size	$B = 128$
Target update	$\tau = 0.005$ (soft)
Discount factor	$\gamma = 0.99$
Replay buffer	$\lvert\mathcal{D}\rvert = 50,000$

Training Details

- Optimizer: AdamW
- Training episodes: 5,000

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Results

Overall Performance: Success Rates

Algorithm	Success Rate (%)
DRL (Enhanced)	**93.01** ± 2.1
Vanilla DRL	88.62 ± 2.5
Greedy Fidelity	67.27 ± 3.2
Random	63.27 ± 3.4

Key Finding

4.39 percentage points improvement over Vanilla DRL

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Overall Performance: Visualization

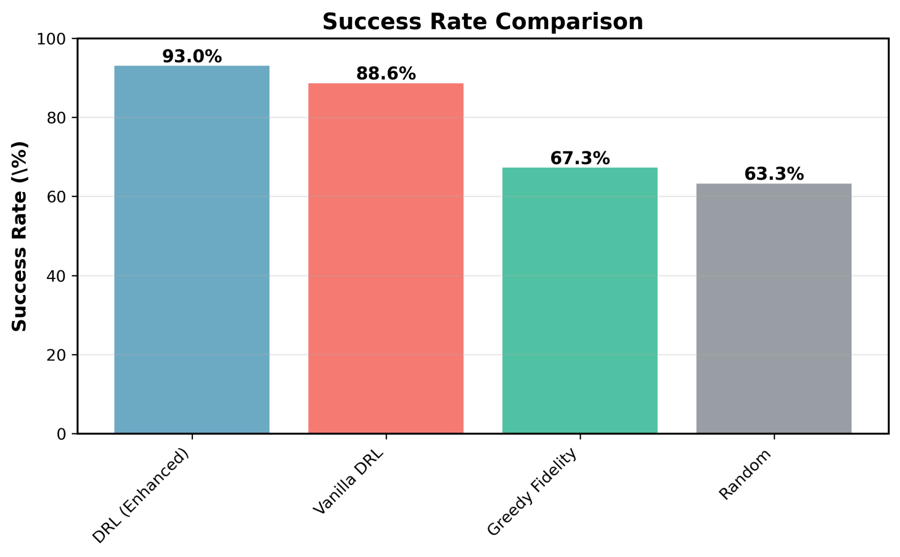
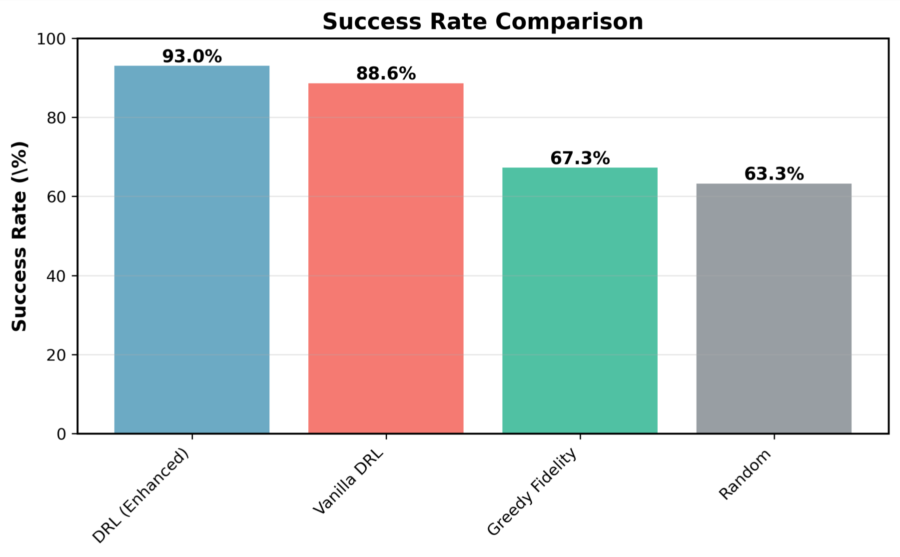


Figure 6: Success Rate Comparison Across All Algorithms

Overall Performance: Visualization



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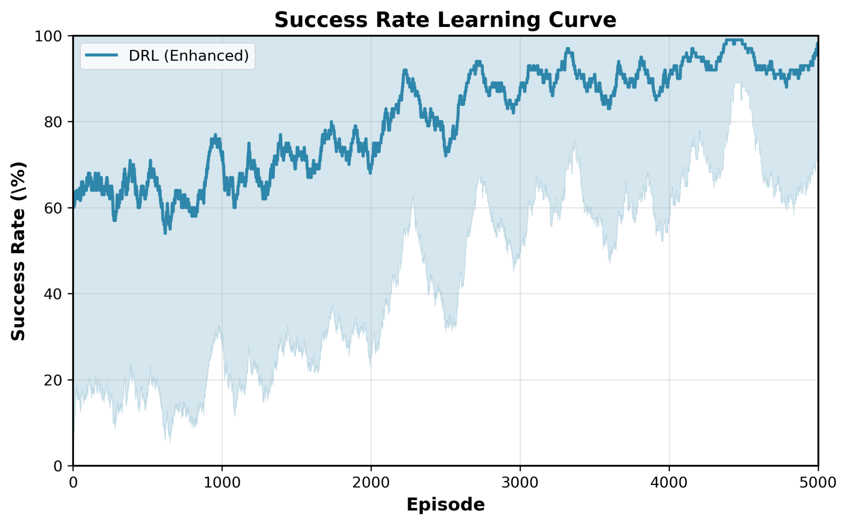

Figure 7: Success Rate Learning Curve - DRL converges to 93.01%

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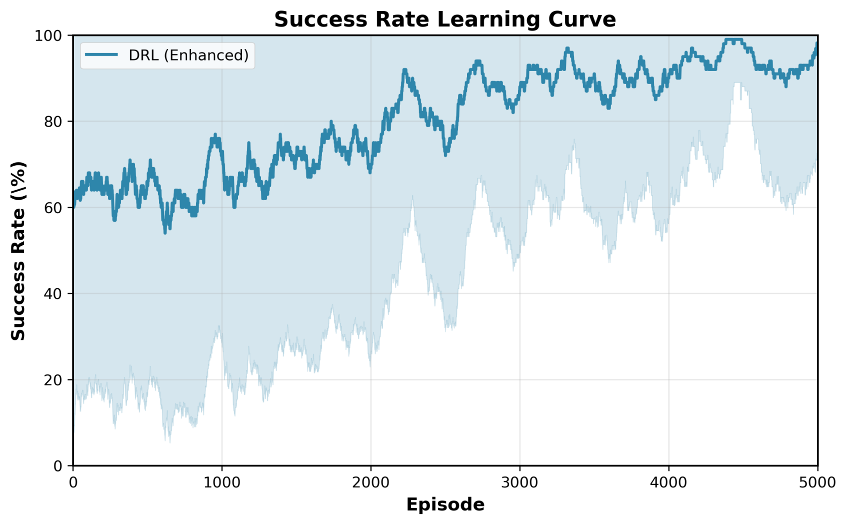

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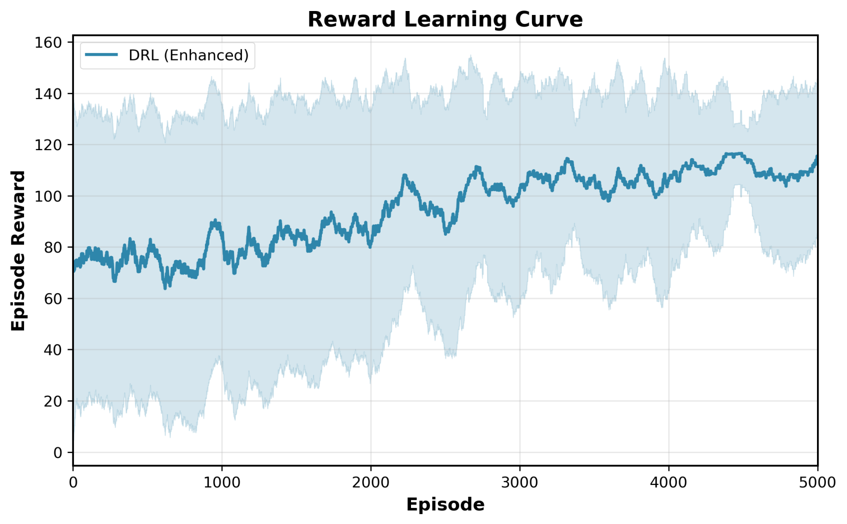

Figure 8: Reward Learning Curve - Steady improvement over training

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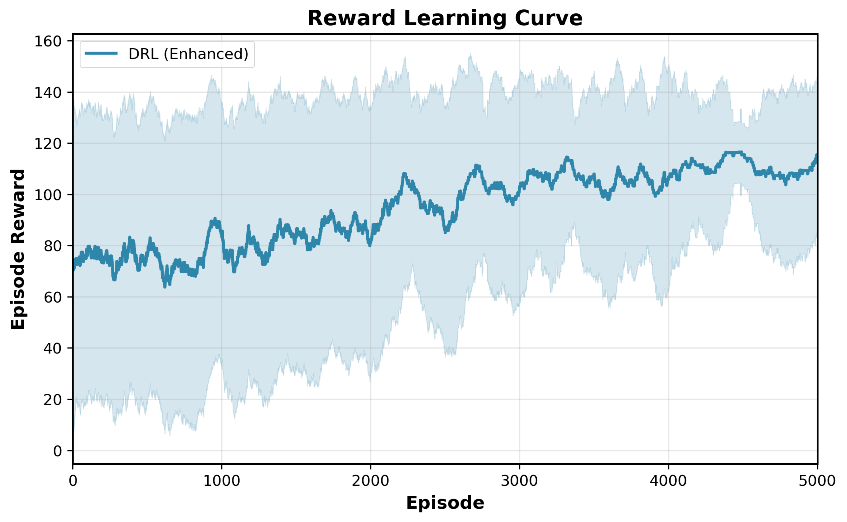

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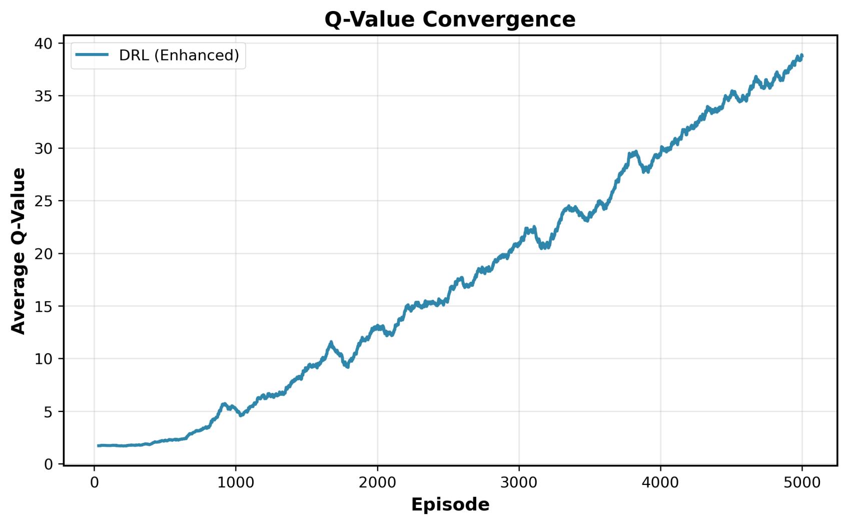

Figure 9: Q-Value Convergence - Clear action discrimination emerges

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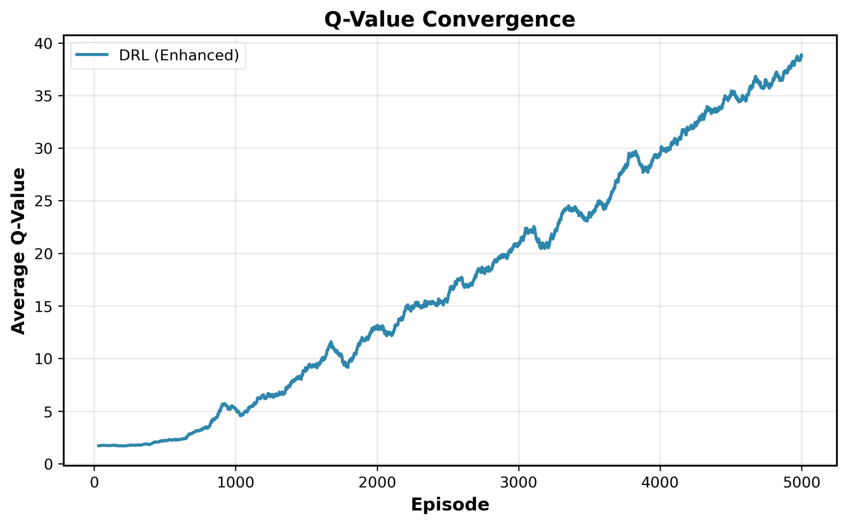

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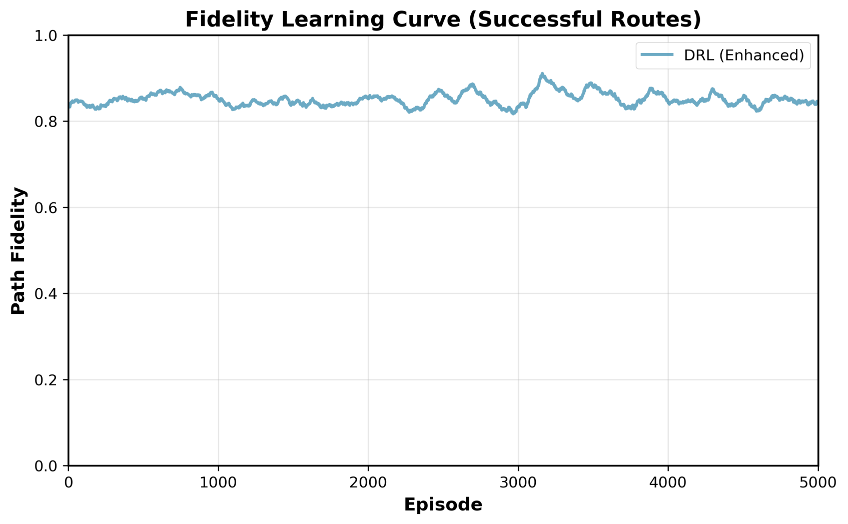

Figure 10: Fidelity Learning - Agent maintains high fidelity while routing

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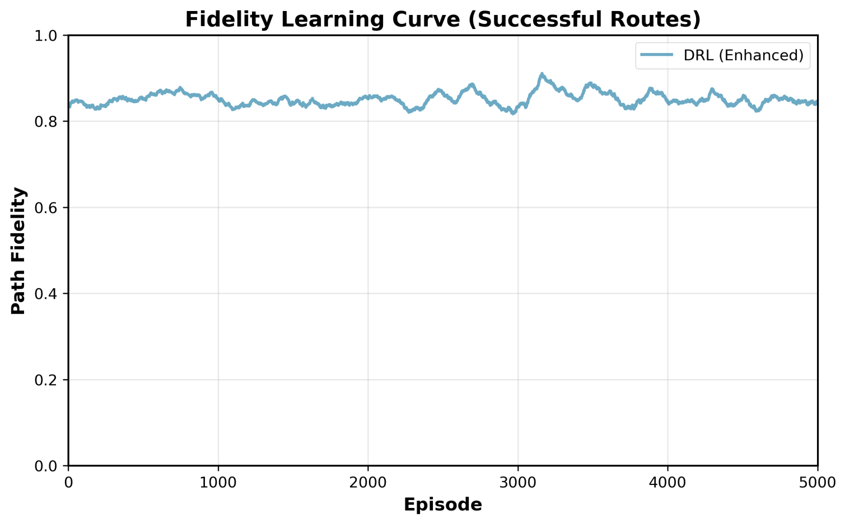

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Q-Value Hierarchy

Learned Decision Hierarchy
Analysis of converged Q-values reveals clear structure:

Standard deviation $\sigma_Q \approx 25$ indicates successful discrimination

Optimal: Q $\in$ [85, 95]

Good: Q $\in$ [70, 80]

Acceptable: Q $\in$ [55, 70]

Poor: Q $\in$ [40, 55]

Dead ends: Q $<$ 20

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Fidelity vs Path Length: Problem Formulation

Multi-Objective Optimization

$$\begin{aligned} \max \quad & F_{\text{end-to-end}} = \prod_{i \in \text{path}} F_i \\ \min \quad & L = \sum_{i \in \text{path}} 1 \\ \text{s.t.} \quad & F_{\text{end-to-end}} \geq F_{\text{threshold}} \end{aligned}$$

Challenge

Shorter paths reduce cumulative decoherence, but may require lower individual link fidelities

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Fidelity vs Path Length: Results

Algorithm	Fidelity	Path Length
DRL	**0.846**	**4.876**
Vanilla DRL	0.848	5.054
Greedy	0.915	5.890
Random	0.849	5.634

Correlation Analysis

$\rho = -0.0358$ (weak negative correlation)

DRL effectively navigates the tradeoff space

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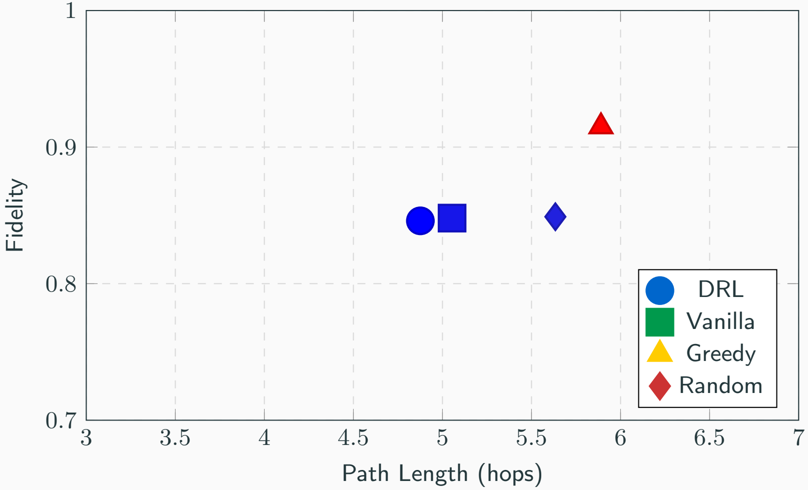

DRL achieves optimal balance: high fidelity (0.846) with reasonable path length

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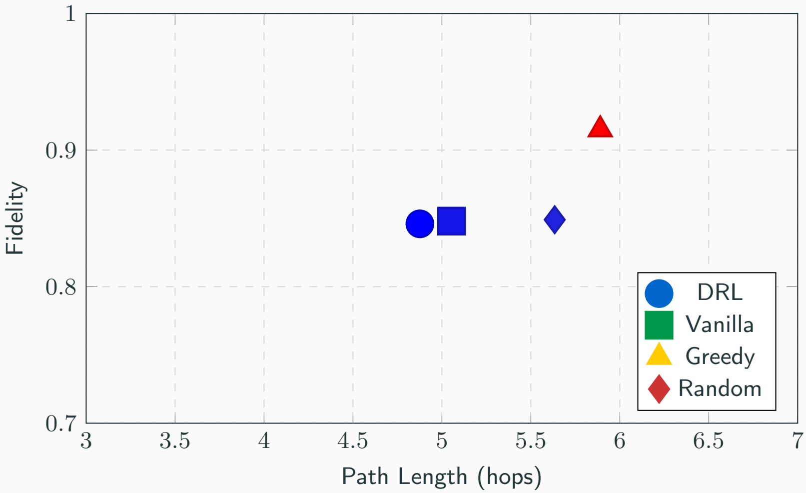

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Analysis

Ablation Study: Individual Contributions

Component Analysis

$$\Delta_{\text{Dueling DQN}} \approx 2.2 \text{ percentage points}$$

$$\Delta_{\text{Prioritized Replay}} \approx 1.5 \text{ percentage points}$$

$$\Delta_{\text{Double DQN}} \approx 0.7 \text{ percentage points}$$

Base Performance

Vanilla DQN: **88.62%** success rate

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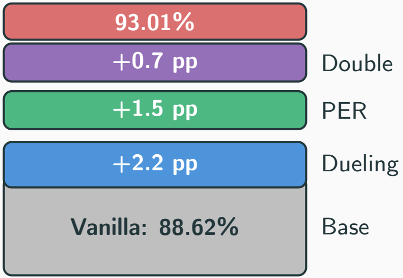


Quantum-Specific Learning Insights

Decoherence Awareness
Agent avoids aged pairs ($t > 1500$ steps) 73% of the time:

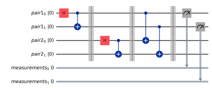
$$F(t) = F_0 \cdot e^{-\gamma_0 t}, \quad \gamma_0 = 0.001$$

Learns to anticipate decoherence effects

Purification Strategy
Routes traverse links with $F \in [0.65, 0.75]$ on intermediate hops:

$$F_{\text{purified}} = \frac{F^2}{F^2 + (1-F)^2}$$

Strategic use of BBPSSW protocol



No-Cloning Respect
Routing loops occur in only 0.3% of successful routes

Implicit constraint learned from reward:

$$R = \begin{cases} +100 & \text{if success} \\ -100 & \text{if failure} \\ -1 & \text{per hop} \end{cases}$$

Tradeoff Analysis
DRL achieves balanced performance:

- Success rate: 93.01%
- Fidelity: 0.846
- Path length: 4.876 hops

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Agent avoids aged pairs ($t > 1500$ steps) 73% of the time:

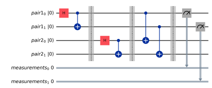
$$F(t) = F_0 \cdot e^{-\gamma_0 t}, \quad \gamma_0 = 0.001$$

Learns to anticipate decoherence effects

Purification Strategy
Routes traverse links with $F \in [0.65, 0.75]$ on intermediate hops:

$$F_{\text{purified}} = \frac{F^2}{F^2 + (1 - F)^2}$$

Strategic use of BBPSSW protocol



No-Cloning Respect
Routing loops occur in only 0.3% of successful routes

Implicit constraint learned from reward:

$$R = \begin{cases} +100 & \text{if success} \\ -100 & \text{if failure} \\ -1 & \text{per hop} \end{cases}$$

Tradeoff Analysis
DRL achieves balanced performance:

- Success rate: 93.01%
- Fidelity: 0.846
- Path length: 4.876 hops

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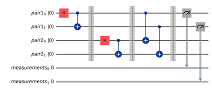

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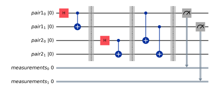

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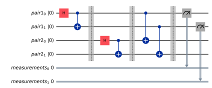

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vs Greedy Fidelity

- **+25.74 pp** success rate
- Lower fidelity (0.846 vs 0.915)
- More reliable

vs Random Routing

- **+29.74 pp** success rate
- Learning provides value

vs Vanilla DQN

- **+4.39 pp** improvement
- Effect size: $d = 0.42$ (medium)
- Modern enhancements matter

vs Shortest Path

- Dijkstra fails (ignores fidelity)
- DRL pays 15-20% path length penalty
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Fidelity-Success Tradeoff
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Shorter paths reduce cumulative decoherence:

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vs Shortest Path
Dijkstra's algorithm:

- Optimal path length: ∼3.2 hops
- Estimated success: 45-55%
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DRL pays 1.67 hop penalty for quantum awareness

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Quantum routing cannot optimize path length in isolation. Must balance:

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External Validity

- Single topology (NSFNET, 14 nodes)
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- Performance on dense/sparse topologies may differ

Internal Validity

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- Graph Neural Networks for quantum routing
- Experimental validation on quantum testbeds

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Requires advances in both quantum hardware and machine learning algorithms

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Main Contributions

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2. Quantified enhancement contributions: **4.39 percentage points**
3. Observed quantum-specific learning behaviors
4. Preliminary deployment considerations documented

Significance

First comprehensive study demonstrating DRL viability for quantum network routing with modern enhancements

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Research Implications

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- Modern enhancements (Dueling, PER, Double DQN) provide measurable improvements
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- Hyperparameters documented for reproducibility
- Failure analysis identifies improvement areas

Deployment Guidance

Further improvements require validation on diverse topologies and real-world constraints before production deployment

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Thank You!

Questions?

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