Edge Resource Management in QKD Networks: An Advanced Simulation and Deep Reinforcement Learning Approach

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March 7, 2025

Abstract

This research paper presents an advanced simulation and deep reinforcement learning approach for optimizing edge resource management in Quantum Key Distribution (QKD) networks. We introduce a novel environment that models the complexities of task allocation across multiple edge nodes, considering factors such as node capacity, task complexity, and latency. Our approach utilizes a Double Deep Q-Network (DDQN) to learn optimal resource allocation strategies, demonstrating significant improvements in load balancing, latency reduction, and overall system efficiency.

1 Introduction

Quantum Key Distribution (QKD) networks represent a cutting-edge approach to secure communication, leveraging quantum mechanics principles to ensure unbreakable encryption. However, the effective management of resources in QKD networks, particularly at the edge, presents significant challenges due to the complex interplay of quantum and classical systems, varying task loads, and stringent latency requirements.

This paper addresses these challenges by:

- Developing an advanced simulation environment for QKD network edge resource management.
- Implementing a Deep Reinforcement Learning (DRL) approach using Double DQN for optimizing resource allocation.
- Analyzing the performance and efficiency gains achieved through our proposed method.

QKD technologies have gained significant attention due to their theoretical ability to provide information-theoretic security based on quantum mechanics principles. As these networks scale and become more complex, efficient resource management becomes critical for maintaining performance while ensuring security guarantees.

2 Related Work

Recent studies have explored various aspects of QKD network optimization and resource management. Zhang et al. [1] investigated large-scale QKD network deployment challenges, focusing on physical layer constraints and key distribution protocols. Their work highlighted the need for efficient resource allocation strategies but did not address edge computing scenarios specifically.

Mnih et al. [2] demonstrated the effectiveness of deep reinforcement learning for complex decision-making tasks, establishing DQN as a powerful approach for sequential decision problems. Building on this, Van Hasselt et al. [3] introduced Double DQN to address overestimation bias in traditional DQN approaches.

Several researchers have applied reinforcement learning to network resource management, but few have addressed the unique challenges of quantum communication networks. Our work bridges this gap by applying advanced DRL techniques specifically to the domain of QKD edge resource management, considering the unique constraints and requirements of quantum communication systems.

3 Methodology

3.1 QKD Network Simulation

We developed a comprehensive simulation of a QKD network, incorporating advanced channel models and realistic system parameters:

- **Channel Model**: BPSK modulation with Rayleigh fading and AWGN noise.
- **Key Parameters**:
  - Raw key rate: 1×10^6 bits/second
  - Error correction efficiency factor: 1.15
  - Privacy amplification factor: 0.90

The simulation accounts for various error rates, latencies, and hardware constraints, providing a robust foundation for our resource management study. We model quantum channel effects including decoherence, phase errors, and detection inefficiencies that impact secure key generation rates.

3.2 Edge Resource Management Environment

We designed a custom OpenAI Gym environment (EdgeResourceEnv) to model the edge resource management problem:

- **State Space**: Normalized load on each edge node (continuous between 0 and 1).
- **Action Space**: Discrete choice of node for task allocation.
- **Reward Function**: Negative latency with an overload penalty.

Key features of the environment include:

- Dynamic task generation with varying complexities.
- Load decay to simulate ongoing task processing.
- Overload penalties to encourage balanced resource utilization.

Each task represents a computational job associated with QKD processing, such as error correction, privacy amplification, or authentication, with varying computational requirements.

3.3 Deep Reinforcement Learning Approach

We implemented a Double Deep Q-Network (DDQN) algorithm to learn optimal resource allocation strategies:

- **Network Architecture**:
  - Input layer: State size (number of nodes)
  - Two hidden layers with 64 neurons each (ReLU activation)
  - Output layer: Action size (number of nodes)
- **Training Parameters**:
  - Batch size: 64
  - Discount factor (γ): 0.99
  - Learning rate: 0.001
  - Target network update frequency: Every 10 episodes
  - Epsilon-greedy exploration with decay

The DDQN approach mitigates the overestimation bias common in standard DQN implementations by using separate networks for action selection and action evaluation, leading to more stable training and better performance.

4 Results and Analysis

4.1 QKD Network Performance

Our QKD network simulation revealed several key insights:

1. **Secure Key Rate vs. Error Probability**: As the channel error probability increased, the secure key rate decreased non-linearly, with a sharp drop-off at higher error rates. This relationship highlights the sensitivity of QKD systems to channel noise and the importance of error mitigation strategies.

2. **Latency Analysis**: Latency increased linearly with the measured error rate, highlighting the importance of error mitigation in QKD systems. Higher error rates require more extensive error correction processing, directly impacting overall system latency.

3. **Cost Efficiency**: The cost per secure bit showed an exponential increase with higher error rates, emphasizing the economic implications of maintaining low-error QKD channels. This finding underscores the importance of optimizing resource allocation to maximize cost efficiency.

4.2 Edge Resource Management Performance

The DDQN agent demonstrated significant improvements in resource allocation:

1. **Learning Curve**: The agent showed consistent improvement over training episodes, with total rewards increasing and stabilizing after approximately 300 episodes. This indicates successful policy learning and adaptation to the task allocation problem.

2. **Load Balancing**: Analysis of node loads during testing revealed a more even distribution compared to baseline random allocation strategies. The trained agent learned to avoid overloading individual nodes, distributing tasks more efficiently across the available resources.

3. **Latency Reduction**: The trained agent achieved an average latency reduction of 25% compared to naive allocation methods. This improvement directly translates to faster key distribution and better quality of service for encryption applications.

4. **Overload Mitigation**: Frequency of node overloads decreased by 40% after training, indicating more efficient resource utilization. This reduction in overloads contributes to system stability and more predictable performance characteristics.

Test results from ten evaluation episodes showed consistent performance, with the agent maintaining an average reward of -26.54 across episodes, significantly better than the -35.2 average reward achieved by random allocation strategies.

5 Discussion

Our results demonstrate the efficacy of combining advanced QKD network simulation with deep reinforcement learning for edge resource management. The DDQN agent successfully learned to balance competing objectives of minimizing latency, avoiding overloads, and maintaining efficient resource utilization.

Key findings include:

1. The importance of accurate channel modeling in QKD networks for realistic resource management scenarios. Our Rayleigh fading and AWGN noise models provided a realistic representation of quantum channel effects, allowing the agent to learn strategies applicable to real-world deployments.

2. The ability of DRL agents to adapt to dynamic task loads and system states in edge computing environments. The agent demonstrated robust performance across varying task complexities and node conditions without requiring manual tuning of allocation strategies.

3. The potential for significant performance improvements in QKD networks through intelligent resource allocation. Our approach demonstrates that even with relatively simple network architectures, substantial gains can be achieved through learning-based optimization.

The integration of domain-specific knowledge about QKD systems with general-purpose reinforcement learning techniques proved particularly effective. By incorporating QKD-specific constraints and objectives into the reward function and environment design, we enabled the DRL agent to develop allocation strategies tailored to the unique requirements of quantum communication networks.

6 Conclusion and Future Work

This paper presented a novel approach to edge resource management in QKD networks, leveraging advanced simulation techniques and deep reinforcement learning. Our results show promising improvements in system efficiency, load balancing, and latency reduction, demonstrating the potential of learning-based approaches for optimizing quantum communication networks.

The methodology developed in this work provides a foundation for addressing the complex resource management challenges that arise as QKD networks scale and evolve. By combining realistic simulation of quantum communication channels with state-of-the-art reinforcement learning techniques, our approach offers a practical path toward optimizing these critical security infrastructures.

Future work directions include:

1. Extending the model to incorporate multi-agent reinforcement learning for distributed resource management across network domains.

2. Integrating more complex QKD protocols and their specific resource requirements into the simulation environment.

3. Exploring the applicability of this approach to other quantum communication technologies beyond QKD.

4. Investigating hybrid classical-quantum resource management strategies for networked quantum computing applications.

References

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