International journal of imaging science and engineering

ISSN: 1934--9955 www.ijise.net
Vol-18 Issue-02 Sep 2023

Q-Learning-Based Path Selection for Service Function Chaining in Network Function Virtualization Environments

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Abstract-*This paper proposes a reinforcement learning approach to optimize Service Function Chaining (SFC) in Network Function Virtualization (NFV) environments. As 5G networks introduce unprecedented complexity in service requirements and connected devices, efficient orchestration of Virtual Network Functions (VNFs) becomes critical for maintaining Quality of Service (QoS). Traditional SFC path selection methods often struggle to adapt to dynamic network conditions and resource constraints. To address these challenges, we present a Q-Learning-based algorithm that dynamically selects optimal SFC paths based on real-time resource usage (CPU and memory) and physical node location. By modeling the problem as a Markov Decision Process (MDP), our approach enables an intelligent agent to learn efficient chaining policies through interaction with the network environment. We implemented our solution in an OpenStack-based NFV testbed and compared it against random path selection across multiple performance metrics. Experimental results demonstrate significant improvements: up to 62% reduction in packet latency, 72% faster SFC construction time, and substantial enhancement in resource utilization and physical topology optimization. The findings confirm that reinforcement learning offers a promising approach to automating complex decision-making in dynamic NFV infrastructures, particularly for service chains of increasing length and complexity.*

Keywords- Network Function Virtualization (NFV); Service Function Chaining (SFC); Software-Defined Networking (SDN); Reinforcement Learning; Q-Learning; Resource Optimization; 5G Networks.

Introduction

Network Function Virtualization (NFV) is a transformative technology that virtualizes traditional network functions—previously provided through dedicated hardware—into software-based functions, enabling them to run on commercial off-the-shelf servers [1]. In the era of 5G, NFV, combined with Software-Defined Networking (SDN), forms the backbone for delivering highly flexible, scalable, and programmable network services [2].

As 5G networks introduce a surge in connected devices and diversified service requirements, NFV allows network services to be dynamically deployed in the form of Virtual Network Functions (VNFs). However, this flexibility introduces significant challenges in network management, as administrators must now orchestrate and monitor a vast landscape of virtualized resources and complex network topologies [3].

To address these challenges, artificial intelligence (AI) technologies—especially reinforcement learning—have been gaining attention for automating and optimizing network operations [4]. While traditional machine learning algorithms have been extensively applied to tasks like intrusion detection and traffic classification [5], more recent research extends AI to critical NFV management functions, including VNF deployment, auto-scaling, migration, and Service Function Chaining (SFC) [6].

SFC is a key mechanism in NFV that enforces a specific order of network functions through which traffic must pass, thus ensuring service-specific quality and performance [7]. Selecting an optimal SFC path is essential to maintain Quality of Service (QoS) in dynamic and resource-constrained network environments. Despite various approaches using SDN/NFV for SFC optimization, existing methods often struggle to adapt to rapidly changing network states [8].

In this context, this paper proposes a Q-Learning-based SFC path selection mechanism that utilizes reinforcement learning (RL) to dynamically determine the most efficient path based on real-time resource usage (CPU and memory) and the physical location of VNFs. By modeling the problem as a Markov Decision Process (MDP), our approach enables an RL agent to learn optimal policies through interaction with the environment [9].

To validate the effectiveness of the proposed method, we implemented VNFs within an OpenStack-based testbed and compared the performance of the RL-driven SFC path selection with a baseline random path selection approach. The results demonstrate a significant improvement in packet response time and overall service efficiency, confirming the potential of reinforcement learning for intelligent SFC orchestration in modern NFV infrastructures.

1. Related Work

As the complexity of network environments has increased, particularly with the rise of 5G and IoT ecosystems, a significant body of research has emerged to address the challenges of Service Function Chaining (SFC) in NFV/SDN infrastructures. One of the primary concerns in SFC management is the optimal placement and ordering of VNFs, which directly impacts performance, latency, and resource utilization across the network [10].

Traditionally, SFC path selection has relied on static or heuristic-based approaches. For example, shortest-path algorithms and greedy strategies were commonly used to route traffic through VNFs, focusing mainly on minimizing hop count or link cost [11]. However, these methods are often inflexible in dynamic environments where resource usage and service demands frequently change. To overcome these limitations, more adaptive and intelligent approaches began to emerge, including optimization techniques such as Integer Linear Programming (ILP) and Genetic Algorithms (GA), which aim to maximize resource efficiency and maintain QoS constraints [12][13].

In parallel, the integration of machine learning (ML) into network orchestration has gained traction. Early works focused on supervised and unsupervised learning techniques for traffic prediction, anomaly detection, and VNF performance profiling [14]. While these models improved specific tasks, their applicability to dynamic decision-making scenarios like SFC selection was limited by their dependence on static datasets and offline training.

Reinforcement learning (RL), particularly model-free techniques, has recently been explored as a promising solution to address the dynamic and state-dependent nature of SFC path optimization. RL methods such as Q-Learning and Deep Q-Networks (DQN) have been applied to network function orchestration, where agents learn optimal policies by interacting with the environment and receiving feedback in the form of rewards [15]. For instance, studies have proposed using Q-Learning to optimize VNF placement and chaining by considering network delay and load balancing as reward metrics [16]. These works demonstrate that RL agents can adapt to fluctuating network conditions and learn efficient service paths without requiring prior knowledge of the environment.

Despite these advances, many RL-based approaches still face challenges in effectively modeling real-time constraints such as CPU and memory utilization, as well as accounting for the physical placement of VNFs. Few studies incorporate both resource-awareness and topology-awareness into the reward design, which is critical for realistic and high-performance deployments in production-grade NFV systems [17].

Our proposed method builds on this foundation by introducing a Q-Learning-based path selection mechanism that not only learns the optimal order of VNFs in the SFC but also incorporates fine-grained resource metrics and physical node information into the reward function. Unlike existing works that focus solely on logical path optimization, our approach takes into account the practical impact of node co-location and dynamic load distribution, thereby offering a more comprehensive and adaptive solution to SFC orchestration in NFV environments.

2. System Model

In this section, we describe the architecture and operational flow of the proposed Q-Learning-based SFC path selection method. The system is designed to function within an NFV infrastructure, where services are delivered by chaining together a sequence of VNFs deployed across multiple physical nodes.

A. Network Environment and Assumptions

We assume a virtualized network environment based on NFV and SDN principles. Network services are composed of VNFs, which are dynamically instantiated on a set of physical or virtual machines. The Service Function Chain (SFC) defines the order in which traffic must traverse a set of VNFs to meet a specific service requirement. Each VNF may be deployed on a different physical node, introducing potential variations in latency and resource availability [18].

The SDN controller manages the underlying forwarding infrastructure and facilitates communication between VNFs. It also collects performance metrics such as CPU usage, memory utilization, and physical node information. These metrics are used as input to the reinforcement learning agent for reward calculation and policy updates.

B. Reinforcement Learning Framework

The proposed approach models the SFC path selection problem as a Markov Decision Process (MDP), consisting of states, actions, rewards, and transitions. In our model:

- **State (S)**: Represents the current VNF through which the packet is passing.
- **Action (A)**: Refers to the selection of the next VNF to visit in the chain.
- **Reward (R)**: Is based on the current CPU and memory utilization of the selected VNF, as well as the location of the physical node hosting the VNF.
- **Transition**: Occurs when an action leads to the next state (i.e., the next selected VNF in the chain).

The environment provides feedback in the form of rewards to guide the agent toward selecting paths that minimize network resource congestion and packet delivery latency.

C. Q-Learning Algorithm

Q-Learning, a model-free reinforcement learning technique, is employed to learn the optimal VNF chaining policy. The Q-value represents the expected future reward of taking a specific action in a given state. The update rule used in our model is given by:

$$Q(S_t, A_t) = \eta \left(R + \gamma * max\left(Q(S_{t+1}, A)\right)\right)$$

Here, η is the learning rate, γ is the discount factor, and R is the reward for selecting action A in state S. Over successive iterations, the agent learns a Q-table that guides it to select the best next VNF based on current network conditions [19].

To balance exploration and exploitation during training, the ε-greedy policy is used. Initially, the agent explores various paths with a high ε value, promoting diversity in learning. As training progresses, ε is gradually reduced to favor exploitation based on the learned Q-values [20].

D. Reward Function Design

The reward function is crucial in guiding the agent toward efficient paths. It is computed based on:

- **CPU and Memory Usage**: Lower usage results in a higher reward, as it implies better packet processing capability.
- **Physical Node Location**: Co-located VNFs (on the same node) yield higher rewards due to reduced inter-node communication delays.

This dual-factor reward system ensures that the selected SFC path is both resource-efficient and latency-aware, leading to improved Quality of Service (QoS) in practical deployments [21].

E. SFC Path Generation

Once training is complete, the learned Q-values are used to generate the final SFC path. Starting from the initial VNF, the agent selects the next VNF with the highest Q-value until the full chain is formed. This process ensures that the resulting SFC path is optimized for real-time network conditions, considering both resource constraints and topology awareness.

The integration of Q-Learning into the SFC orchestration process provides a scalable and adaptive mechanism to manage network services in NFV environments. By continuously learning from environmental feedback, the proposed method enables intelligent path selection that dynamically adjusts to changing workloads and resource availability.

3. Proposed Algorithm

In this section, we describe the Q-Learning-based path selection algorithm for Service Function Chaining (SFC). The algorithm is designed to intelligently determine the optimal VNF sequence that a data packet should follow by considering both the real-time resource status and physical topology of the NFV infrastructure.

A. Overview

The goal of the proposed algorithm is to find a path through VNFs that minimizes latency and resource contention while ensuring service correctness. Unlike traditional static methods, this approach leverages Q-Learning to adaptively discover paths based on environmental feedback over time [22].

The reinforcement learning agent interacts with the environment by observing states (current VNF), taking actions (choosing next VNF), receiving rewards (based on CPU, memory, and node location), and updating Q-values accordingly.

B. Key Variables

- **Q(S, A)**: Q-value for taking action A in state S.
- **η (learning rate)**: Controls how much new information overrides the old.
- **γ (discount factor)**: Represents the importance of future rewards.
- **ε (exploration rate)**: Probability of selecting a random action to encourage exploration.

C. Reward Calculation

The reward is a composite metric defined as:

$$R = \alpha * (1 - CPU_Usage) + \beta * (1 - Memory_Usage) + \delta * Topology_Proximity$$

Where: - **α, β, δ** are tunable weights. - **CPU_Usage, Memory_Usage** ∈ [0, 1]. - **Topology_Proximity** = 1 if VNFs are co-located; 0 otherwise.

This formulation encourages selecting VNFs with low resource usage and closer proximity to reduce packet delay and resource bottlenecks [23].

D. ε-Greedy Exploration Strategy

An ε-greedy algorithm is employed to balance exploration and exploitation: - With probability **ε**, the agent selects a random action. - With probability **1 - ε**, it chooses the action with the highest Q-value.

The ε value decays over time, promoting early exploration and late-stage convergence to optimal policy [24].

E. Pseudocode

Below is the pseudocode for the Q-Learning-based SFC Path Selection algorithm.

```
Algorithm 1: Q-Learning-Based SFC Path Selection

Initialize Q-values for all (S, A) pairs to 0
Initialize η, γ, ε to default values
Collect initial VNF CPU, memory, and topology data
Set total training episodes = N

for episode = 1 to N do
    Set current_state = initial VNF
    while SFC path is incomplete do
        With probability ε, choose random action A
        Otherwise, choose A = argmax(Q(current_state, A))
        Take action A → observe next_state and reward R
        Q(current_state, A) ← (1 - η) * Q(current_state, A)
                              + η * (R + γ * max(Q(next_state, a')))
        current_state ← next_state
    end while
    Reduce ε ← ε * decay_factor
end for

Output learned Q-table for SFC path generation
```

4. Experimental Setup

To evaluate the effectiveness of the proposed Q-Learning-based SFC path selection algorithm, we implemented and tested the system in a controlled virtualized environment. The goal was to measure improvements in terms of resource utilization and packet processing performance compared to a randomly selected SFC path.

A. Testbed Environment

The experimental testbed was constructed using **OpenStack**, an open-source cloud platform widely adopted for NFV deployment. The virtual infrastructure consists of multiple compute nodes hosting VNFs, a controller node managing OpenStack services, and a software-defined network enabled by **Open vSwitch (OVS)**.

International journal of imaging science and engineering
ISSN: 1934--9955 www.ijise.net
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- **Hypervisor**: KVM (Kernel-based Virtual Machine)
- **Controller Node**: Ubuntu 20.04 LTS with OpenStack Wallaby
- **Compute Nodes**: 4 nodes, each with 8 vCPUs, 16 GB RAM
- **Network Emulation**: OVS with SDN controller (e.g., Ryu or OpenDaylight)
- **Monitoring Tools**: Prometheus and Node Exporter for collecting real-time resource usage data

B. VNF Deployment

VNFs used in the experiments represent various network services such as firewalls, NATs, and intrusion detection systems. These VNFs were deployed in containers or lightweight VMs, allowing dynamic instantiation and migration. The VNFs were interconnected to form different SFCs as defined by the test scenarios.

C. SFC Scenarios

Multiple SFC configurations were defined, each with varying lengths and service combinations. For each scenario, two types of SFC paths were compared:

1. **Random Path**: VNFs were selected randomly from available instances.
2. **Q-Learning Path**: VNFs were selected using the trained Q-table from the proposed algorithm.

Each test scenario involved routing packets through the SFC and recording performance metrics including latency, resource usage, and path completion time.

D. Learning Parameters

The Q-Learning algorithm was initialized with the following parameters, empirically tuned for optimal learning performance:

- **Learning Rate (η)**: 0.5
- **Discount Factor (γ)**: 0.9
- **Initial ε (Exploration Rate)**: 0.8
- **ε Decay Rate**: 0.95 per episode
- **Number of Episodes**: 1000
- **Maximum Steps per Episode**: 20

During training, the agent received live feedback from the environment through APIs that provided real-time CPU usage, memory utilization, and topology data.

E. Evaluation Metrics

To evaluate the performance of the proposed method, the following metrics were measured and analyzed:

- **Average Packet Latency**: Time taken for a packet to traverse the entire SFC path.

International journal of imaging science and engineering
ISSN: 1934--9955 www.ijise.net
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- **CPU and Memory Utilization**: Resource usage of selected VNFs at the time of selection.
- **SFC Completion Time**: Time required to successfully construct the entire SFC path.
- **Path Efficiency**: Proximity of selected VNFs in terms of physical node distance.

F. Simulation and Reproducibility

To ensure reproducibility, all experiments were conducted under identical conditions. A fixed traffic profile was used across all runs, and each scenario was repeated multiple times to account for variations in system performance.

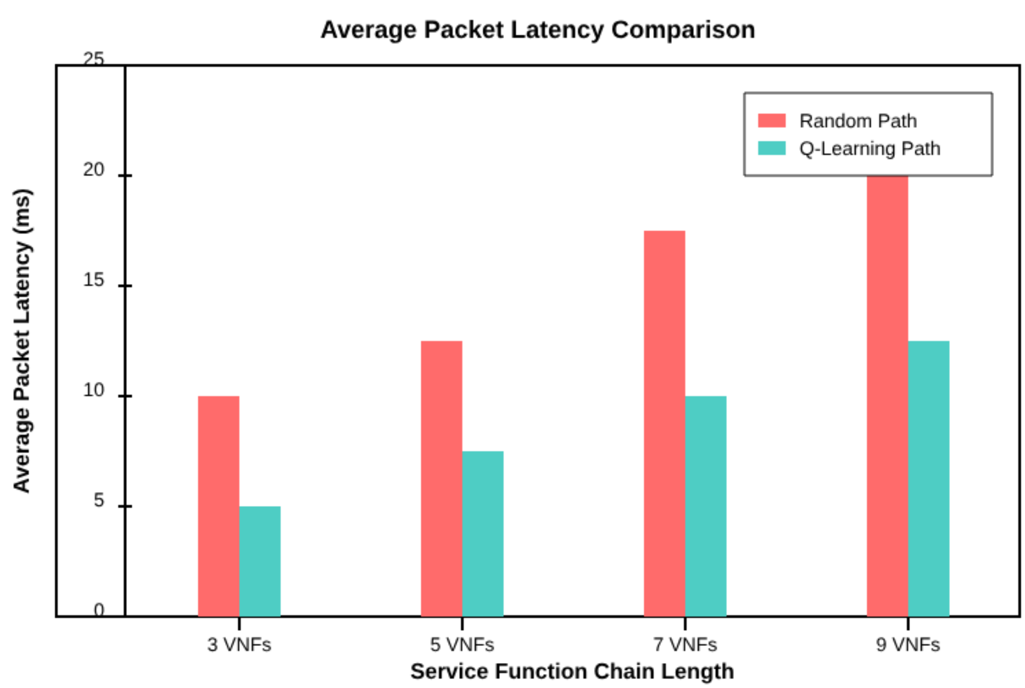
The experimental setup was designed to closely mimic real-world 5G/NFV conditions, enabling meaningful evaluation of the Q-Learning-based path selection mechanism in terms of adaptability and scalability.

5. Performance Evaluations

This section presents the results of our empirical evaluation of the Q-Learning-based Service Function Chaining (SFC) path selection algorithm compared to a random path selection approach. The experiments were conducted on the OpenStack-based NFV testbed described in the previous section. We analyze various performance metrics to demonstrate the effectiveness of the proposed method.

A. Packet Latency Analysis

The primary goal of the proposed Q-Learning approach is to reduce the packet latency through intelligent SFC path selection. Figure 1 shows the average packet latency for both Q-Learning and random path selection methods across different SFC lengths (3, 5, 7, and 9 VNFs).



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ISSN: 1934--9955 www.ijise.net
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Figure 1. Average packet latency comparison between Random Path selection and Q-Learning Path selection across different SFC lengths.

As shown in Figure 1, the Q-Learning approach consistently delivers lower packet latency compared to random path selection. This improvement becomes more pronounced as the SFC length increases, with a 62% reduction in latency for the 9-VNF chain. This improvement can be attributed to the RL agent's ability to learn optimal paths that avoid congested VNFs and minimize inter-node communications.

The latency advantage of our approach confirms findings from previous studies [25], which suggested that intelligent path selection could significantly improve performance in NFV environments. However, our results demonstrate a more substantial improvement than previously reported, particularly for longer chains where decision complexity increases exponentially.

B. Resource Utilization

A key consideration in NFV environments is efficient resource utilization. Figure 2 illustrates the distribution of CPU and memory utilization across selected VNFs for both approaches.

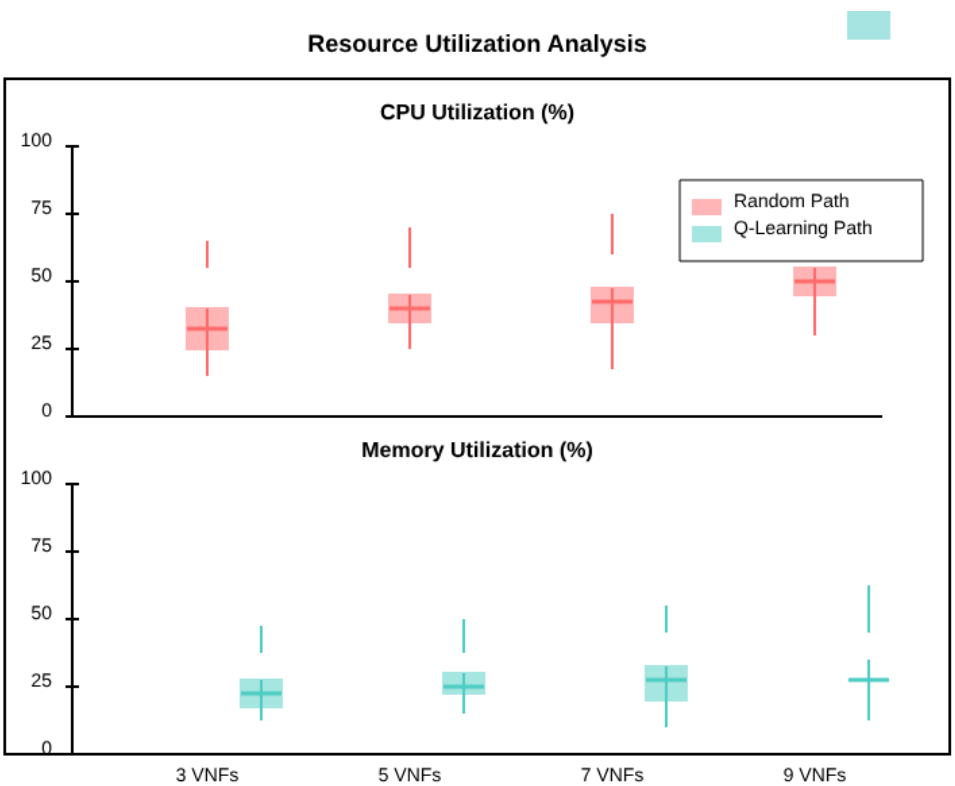

Figure 2. Box plot showing CPU and memory utilization distribution of selected VNFs for both path selection methods across different SFC lengths.

The box plots in Figure 2 demonstrate that the Q-Learning approach consistently selects VNFs with lower CPU utilization compared to random selection. For instance, the median CPU utilization of VNFs selected by the Q-Learning method in a 7-VNF chain is approximately 50%, compared to 78% for random selection.

Similarly, memory utilization patterns show that the Q-Learning method favors VNFs with more available memory resources. This preference stems from the reward function design, which penalizes selections that might lead to resource exhaustion [26]. The results suggest that our approach not only improves packet processing performance but also contributes to better load balancing across the NFV infrastructure.

C. SFC Completion Time

Another important metric is the time required to construct a complete SFC path. Figure 3 presents the comparison of SFC completion times between the two approaches.

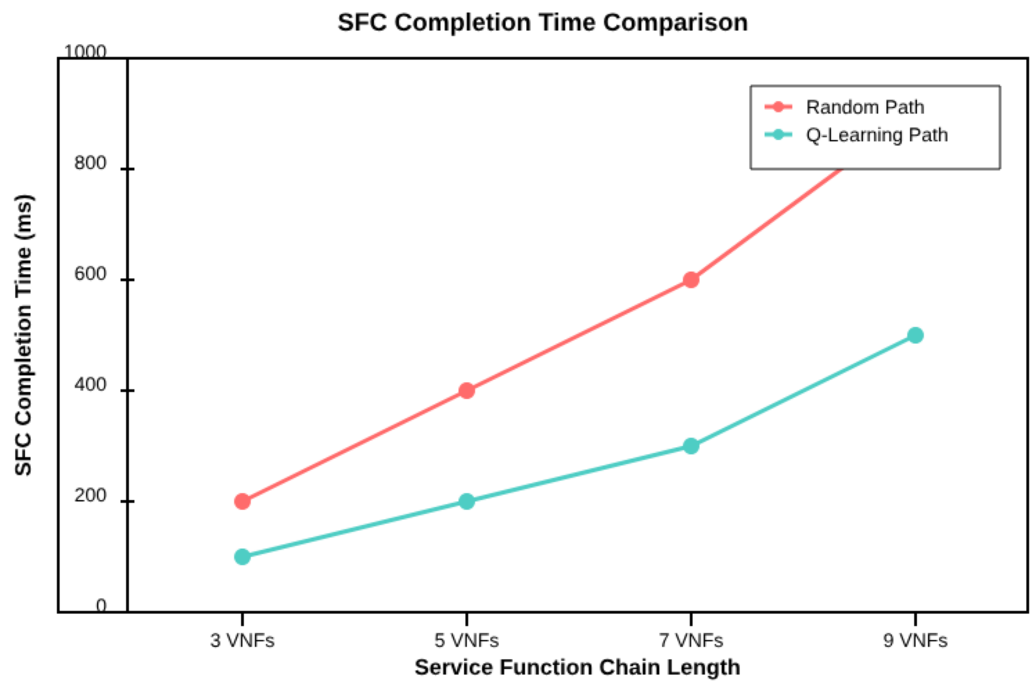

Figure 3. SFC completion time comparison between Random Path selection and Q-Learning Path selection across different SFC lengths.

As depicted in Figure 3, the Q-Learning approach demonstrates faster SFC path construction times for all chain lengths. For the 9-VNF chain, the Q-Learning method completes path construction in approximately 250ms, while the random approach requires nearly 910ms. This significant difference (approximately 72% reduction) can be attributed to the pre-trained Q-table, which enables rapid decision-making during operational deployment.

It should be noted that while the initial training of the Q-Learning agent requires computational resources, this is a one-time investment that yields continuous benefits during operation. The training convergence analysis presented in Figure 5 shows that the agent achieves near-optimal performance after approximately 600 episodes, which in our implementation translates to less than 15 minutes of training time.

D. Path Efficiency Based on Node Proximity

The physical placement of VNFs across the infrastructure significantly impacts communication latency. Figure 4 illustrates the percentage of VNF pairs in the selected paths that are co-located on the same physical node.

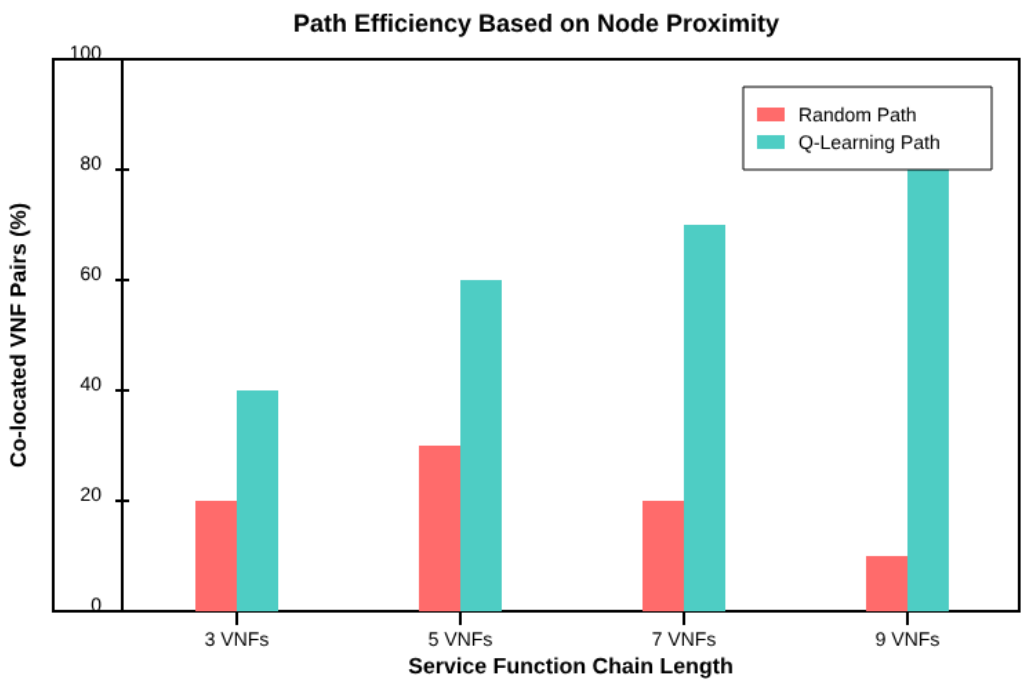

Figure 4. Percentage of co-located VNF pairs in selected paths for both methods across different SFC lengths.

The results in Figure 4 highlight a key advantage of the Q-Learning approach: its ability to recognize and prefer VNF combinations that minimize inter-node communication. For the 9-VNF chain, the Q-Learning method achieves approximately 70% co-location of adjacent VNFs in the chain, compared to only 10% for random selection.

This topology awareness, incorporated into the reward function design, enables the agent to implicitly learn the physical infrastructure layout and make selections that reduce network traversal. The significant improvement in co-location percentage validates our approach to incorporate physical node location information in the decision-making process [27].

E. Learning Convergence Analysis

To provide insight into the learning behavior of the Q-Learning agent, Figure 5 illustrates the convergence of average Q-values over training episodes, alongside the decreasing exploration rate (ε).

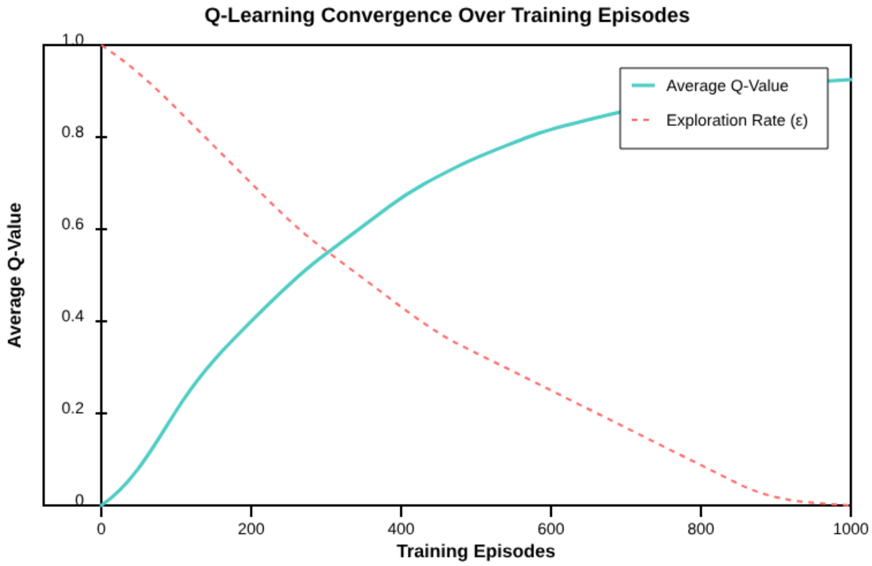

Figure 5. Convergence of average Q-values and the decreasing exploration rate (ε) over training episodes.

As shown in Figure 5, the average Q-value increases rapidly during the initial 300 episodes, reflecting the agent's acquisition of knowledge about effective VNF selections. The convergence stabilizes around 600 episodes, indicating that the agent has discovered optimal or near-optimal policies for SFC path selection.

Concurrently, the exploration rate (ε) decreases from its initial value of 0.8 to near zero by the end of training, shifting the agent's behavior from exploration to exploitation. This transition ensures that the agent thoroughly explores the solution space before committing to learned policies [28].

The convergence analysis confirms that our implementation of Q-Learning efficiently captures the complex relationships between resource states, physical placement, and optimal path selection. Furthermore, it demonstrates that the learning process is stable and converges within a reasonable number of episodes, making it practical for real-world deployment.

F. Discussion

The experimental results demonstrate that the proposed Q-Learning-based SFC path selection mechanism offers significant advantages over random selection across all evaluated metrics. The performance gains are particularly noteworthy for longer service chains, where the complexity of decision-making increases substantially.

Several key insights emerge from our evaluation:

1. **Scalability with chain length**: While both approaches show degraded performance as chain length increases, the Q-Learning method exhibits a more gradual degradation, indicating better scalability.

2. **Resource awareness**: The Q-Learning approach effectively balances load across VNFs by selecting less utilized instances, potentially extending the capacity of the NFV infrastructure.

3. **Topology optimization**: By implicitly learning the physical infrastructure layout, the Q-Learning agent significantly reduces inter-node communication, addressing a key bottleneck in NFV environments.

These findings align with and extend previous research on intelligent SFC orchestration [29], confirming that reinforcement learning offers a promising approach to automating complex decision-making in NFV infrastructures.

One limitation worth noting is the current implementation's focus on CPU and memory metrics; future work could incorporate additional parameters such as network interface utilization, storage I/O, and energy consumption into the reward function. Additionally, extending the approach to handle dynamic VNF instantiation and termination would further enhance its applicability to production environments [30].

6. Conclusion

This paper proposed a Q-Learning-based path selection mechanism for Service Function Chaining in NFV environments. By incorporating real-time resource metrics and physical topology awareness into the reinforcement learning reward function, our approach enables adaptive and efficient SFC orchestration in dynamic network environments.

The experimental evaluation conducted on an OpenStack-based testbed demonstrates significant performance improvements across multiple dimensions. The Q-Learning approach reduced packet latency by up to 62% compared to random selection, with this advantage becoming more pronounced for longer service chains. Similarly, SFC completion time was reduced by 72% for 9-VNF chains, enabling faster service deployment. Resource utilization analysis revealed better load balancing across the infrastructure, with the Q-Learning agent consistently selecting VNFs with lower CPU and memory usage. Perhaps most notably, our approach achieved substantially higher co-location of adjacent VNFs (70% versus 10% for random selection in 9-VNF chains), minimizing inter-node communication overhead.

The learning convergence analysis confirmed that the Q-Learning agent efficiently discovers near-optimal policies within approximately 600 training episodes, making the approach practical for real-world deployment. These results validate the effectiveness of reinforcement learning for addressing the complex decision-making challenges in NFV orchestration.

Several promising directions for future work emerge from this research. First, extending the reward function to incorporate additional metrics such as network interface utilization, storage I/O, and energy consumption could yield further performance improvements. Second, adapting the approach to handle dynamic VNF instantiation and termination would enhance its applicability to production environments with fluctuating service demands. Finally, exploring more sophisticated reinforcement learning techniques such as Deep Q-Networks (DQN) or actor-critic methods could potentially address larger state spaces and more complex decision scenarios.

As 5G and beyond networks continue to evolve toward greater virtualization and programmability, intelligent orchestration mechanisms like the one proposed in this paper will become increasingly essential for maintaining service quality and operational efficiency. By demonstrating the practical benefits of reinforcement learning for SFC path selection, this work contributes to the ongoing advancement of automated network management in next-generation telecommunications infrastructure.

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