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Resource and Topology Aware Q-Learning for Service Function Chaining in NFV 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.

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

I. 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].

II. 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.

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.

- **Q(S, A)**: Q-value for taking action A in state S.
- **η (learning rate)**: Controls how much new information overrides the old.

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- **γ (discount factor)**: Represents the importance of future rewards.
- **ε (exploration rate)**: Probability of selecting a random action to encourage exploration.

The reward is a composite metric defined as:

$$R = \alpha * (1 - \mathrm{CPU}_{\mathrm{U}}\mathrm{sage}) + \beta * (1 - \mathrm{Memory}_{\mathrm{U}}\mathrm{sage}) + \delta * \mathrm{Topology}_{\mathrm{P}}\mathrm{roximity}$$

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].

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].
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
```

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)**.

- **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

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.

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.

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

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- **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.
- **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.

III. 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.

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).

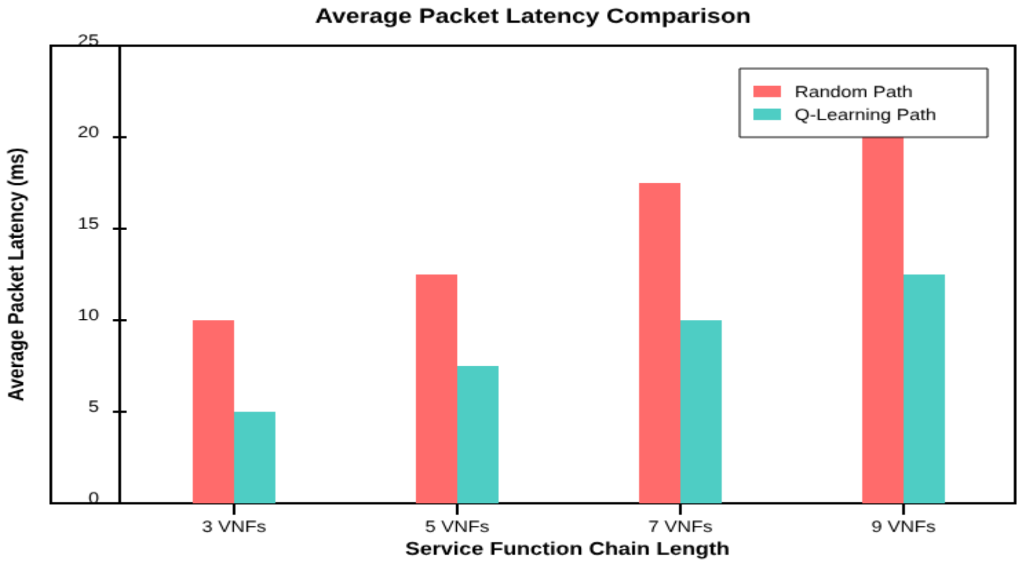

Figure 1. Average packet latency comparison between Random Path selection and Q-Learning Path selection across different SFC lengths.

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

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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.

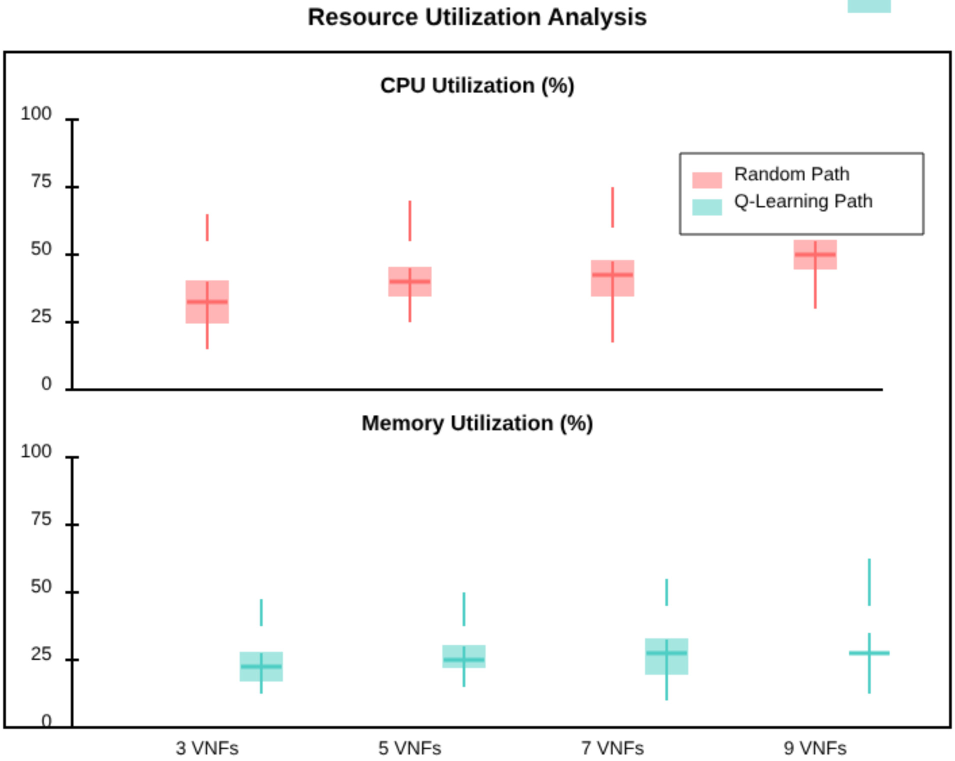

Figure 2. Box plot showing CPU and memory utilization distribution of selected VNFs for both path selection methods across different SFC lengths.

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.

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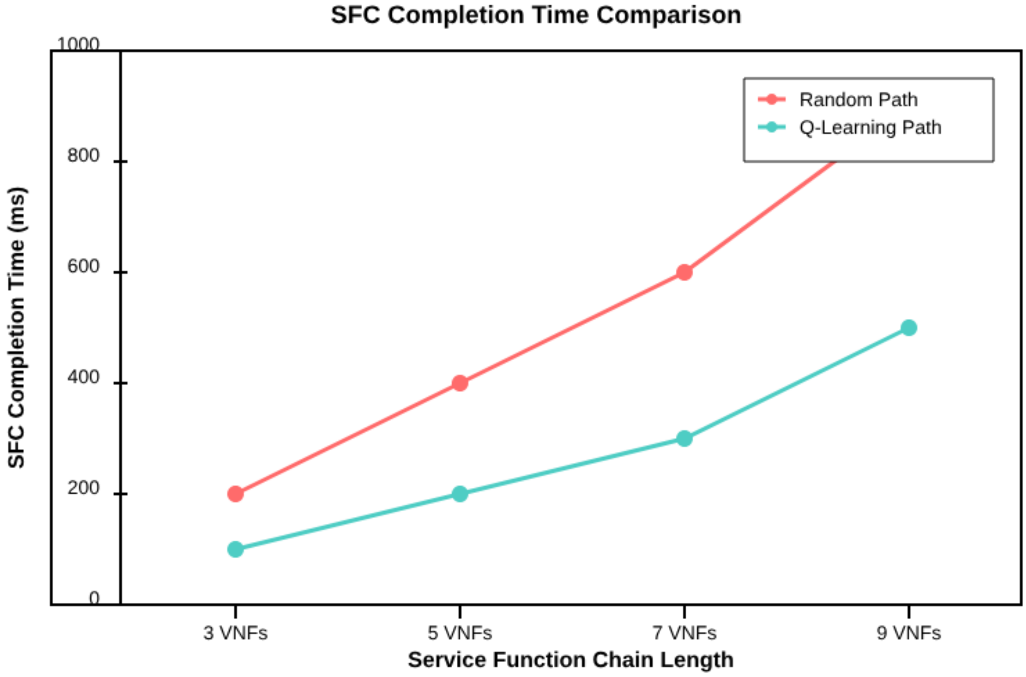

Figure 3. SFC completion time comparison between Random Path selection and Q-Learning Path selection across different SFC lengths.

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.

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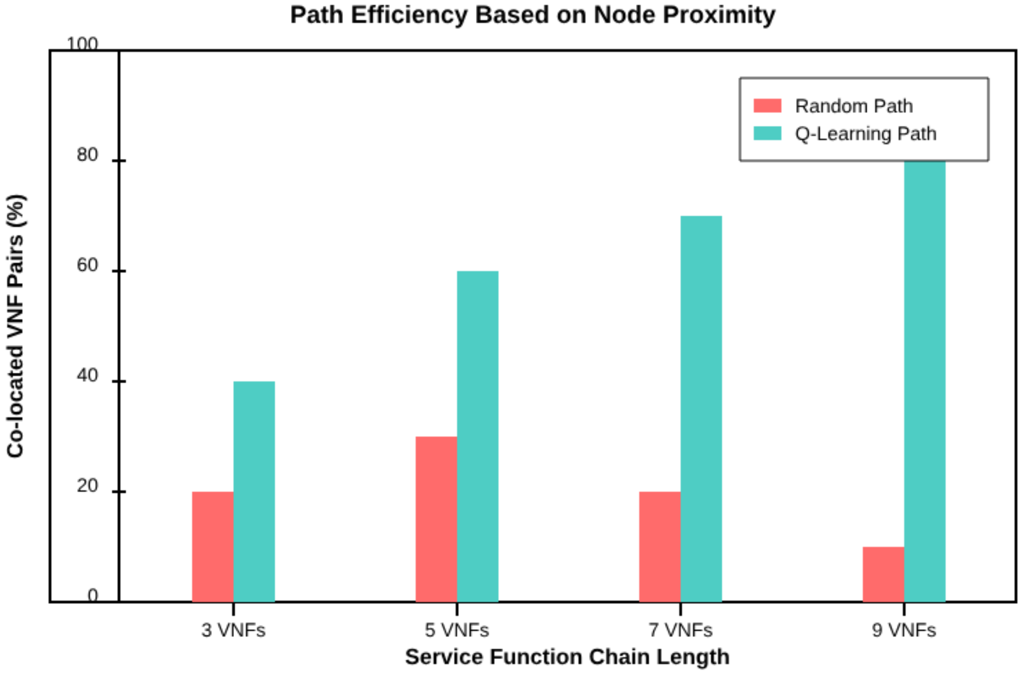

Figure 4. Percentage of co-located VNF pairs in selected paths for both methods across different SFC lengths.

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.

IV. 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.

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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