Paradigm Academic Press
Innovation in Science and Technology
ISSN 2788-7030
NOV. 2023 VOL.2, NO.6

Research on Reliable Deployment Algorithm for Service Function Chain Based on Deep Reinforcement Learning

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doi:10.56397/IST.2023.11.01

Abstract

This paper investigates the reliable deployment algorithm for Service Function Chains (SFC) based on deep reinforcement learning. SFC, as a chained function composition for complex network services, plays a crucial role in improving network efficiency and stability. To address the issue of existing SFC deployment algorithms that overlook the reliability of network functions and links, this paper proposes a deep reinforcement learning-based algorithm that utilizes a virtual network function and virtual link reliability mapping model for optimization. By learning the mapping between system states and actions, the algorithm can optimize the deployment strategy of SFC, thereby enhancing its reliability and performance. Experimental results demonstrate that the proposed algorithm can significantly improve the reliability of SFC and have practical implications for network service deployment.

Keywords: deep reinforcement learning, service function chaining, reliable deployment algorithms

1. Introduction

With the rapid development of cloud computing and network technologies, Service Function Chain (SFC) has emerged as a promising network architecture for implementing complex network services. SFC connects multiple network function instances in a specific order to meet different business requirements and provide efficient network services. However, the current SFC deployment algorithms still face challenges in considering the reliability of the function chain. Ensuring the reliable deployment of SFC is crucial for improving network efficiency and stability, which requires taking into account the reliability requirements of network functions and links. Specifically, the reliability requirements of virtual network functions and the mapping of links between functions play a key role in the overall system performance. Therefore, it becomes an urgent issue to optimize SFC deployment through well-designed algorithms while considering reliability to enhance its performance. In summary, this research paper is significant for addressing the reliable deployment issue of SFC and improving network efficiency and stability (Fang B & Guo T., 2022). Through in-depth analysis of the SFC system model, proposing innovative algorithms, and conducting experimental validations, we aim to provide new insights and methods for the reliable deployment of SFC, as well as theoretical foundations and practical guidance for optimizing and enhancing network functions.

2. Service Function Chain System Model

In this paper, we study the basic model of providing end-to-end services in a network virtualization environment. As shown in Figure 1, the end-to-end service function chain starts from the end devices and deploys virtual network functions (VNFs) in a sequential manner through the access network and the core network to meet the corresponding business requirements. The figure illustrates two slices, with SFC1 representing the service function chain of Slice 1 and SFC2 representing the service function chain of Slice 2.

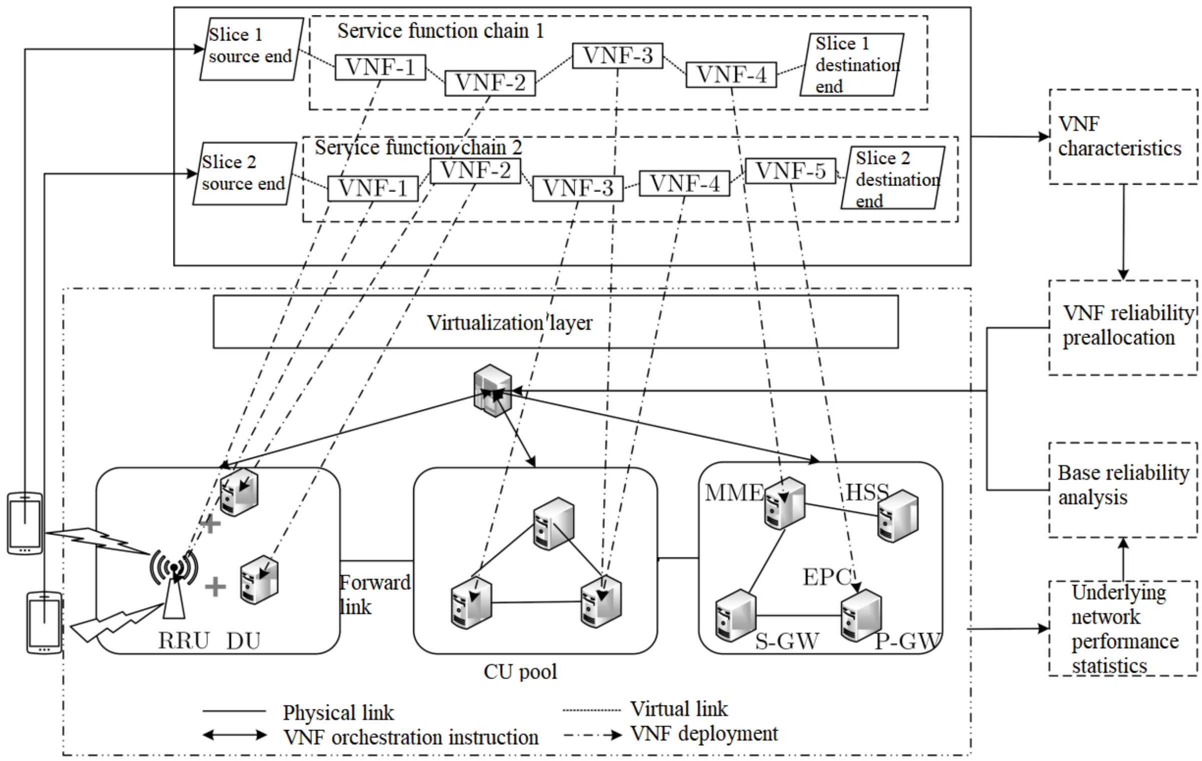

Figure 1. Scenario diagram of the system

The virtual subnets composed of these service function chains are constructed and managed by Service Providers (SPs). To achieve global management, SPs can utilize a Global Service Orchestrator (GS-O) to coordinate the deployment and configuration of each service function chain. The GS-O is responsible for service orchestration and coordination to ensure the smooth operation of the entire network. On the other hand, Infrastructure Providers (InPs) are responsible for building and maintaining the underlying physical infrastructure. InPs provide reliable resources to SPs through standardized interfaces in accordance with the resource requests from SPs, supporting the deployment and operation of service function chains (Xi S, Xiaoqin Z, Yong Y, et al., 2022).

In this system model, SPs and InPs cooperate and interact to provide services and allocate resources. SPs rely on the GS-O to manage and orchestrate service function chains, while InPs provide reliable infrastructure to support the deployment and operation of service function chains. This collaborative model allows end-to-end service function chains to be flexibly and reliably delivered to end users. By studying this service function chain system model, we can gain a better understanding of the basic architecture and operation mechanisms of service provision in virtualized network environments. This helps us further explore and optimize reliable deployment algorithms for service function chains, enhancing network performance and efficiency.

3. Virtual Network Function and Virtual Link Reliability Mapping Models

3.1 Virtual Network Function Reliability Requirement Determination Model

In an SFC, each Virtual Network Function (VNF) has different topological and functional characteristics, resulting in varying impacts, recovery difficulties, and recovery time in the event of failures. To determine the importance of each VNF in case of failures and further establish their corresponding reliability requirements, this paper presents a model for determining the reliability requirements of virtual network functions (Li H, Ao C, Xu Y, et al., 2016).

To achieve this goal, it is necessary to consider some reference features that possess different dimensions and require normalization. Here are some explanations of the reference features:

1) VNF sharing degree: Due to functional reuse, a single VNF may be shared by multiple SFCs. If a shared VNF fails, it will impact all related services. Therefore, the degree of VNF sharing determines its importance. In this paper, the number of SFCs that share the same VNF is defined as the VNF sharing degree (ψ). To avoid excessive sharing that would increase the probability of shared failures, the maximum sharing degree is set to 4. The normalized result is represented as shown in Formula (1).

$$z_I^1 = \psi / 4 \tag{1}$$

2) Recovery cost: Each VNF incurs corresponding resource consumption during recovery, and the higher the resource demand, the lower the likelihood of recovery. Therefore, VNFs with high resource requirements need higher reliability. The normalized result is represented as shown in Formula (2).

$$z_I^2 = c_{vI}^k / \max_{v_I^k} c_{vI}^k, c_{vI}^k \in v_k \tag{2}$$

3) VNF functional importance: Different VNFs have different degrees of functional importance for Infrastructure Providers. For example, VNFs involved in global control and data processing in the core network are relatively more important compared to VNFs in the access network. Based on experience, the functional importance of each VNF can be determined, and higher reliability requirements can be assigned accordingly. Let the importance score be x_I, recorded in a scoring table. The normalized result is represented as shown in Formula (3).

$$z_I^3 = \chi_I - \max_I \chi_I / \max_I \chi_I - \min_I \chi_I \tag{3}$$

4) VNF state: VNF states can be categorized as relevant states and unrelated states. Unrelated states are modified as data flows arrive and are processed, requiring more time and cost for recovery. Therefore, VNFs in unrelated states require higher reliability. In this paper, unrelated states are assigned a value of 1 in the VNF state, while the absence of unrelated states is assigned 0.5.

By conducting a comprehensive analysis and normalization of these reference features, we can determine the importance of each VNF in the event of failures and further establish their corresponding reliability requirements. This will help us formulate reasonable deployment strategies to enhance the reliability of virtual network function chains (Yanghui, Fu, Xingxing, et al., 2020).

3.2 Reliable Mapping Model for Links Based on Functional Multiplexing

The research in this paper considers the joint optimization of functional reuse and functional deployment as well as bandwidth requirements, aiming to find the optimal balance between functional reuse and path length. To achieve this goal, the deployment problem is decomposed into two key steps.

First, we need to set the maximum value of the number of transmission hops u'_k . The number of transmission hops is the number of network nodes to be traversed in the path. The length of the path is closely related to the multiplexing of the link, since longer paths tend to reduce the reliability of the link. Therefore, we can try to satisfy the link reliability requirement by controlling the link length u'_k . Thus, it can be obtained as shown in Formula (4):

$$u_k = [\log_{r_l R_L^k}]^+ \tag{4}$$

Where []+ denotes upward rounding, r_l is the average reliability of the base link, denoted as shown in Formula (5), where |L| denotes the number of base links.

$$r_l = \sum_{l_{i,j} \in L} RL(l_{i,j}) / |L| \tag{5}$$

After determining the range of transmission hops, the next crucial step is to find the path with the highest degree of reuse within this range. Reuse degree refers to the number of network resources and links that can be reused along the path. When the reuse degree of a path is high, we can optimize resource utilization to the maximum extent and meet the bandwidth requirements of various services (Zhao T, Wang P & Li S., 2020).

In the link reliability mapping model based on functional reuse, our goal is to achieve reliable deployment of function chains and satisfy the bandwidth requirements by selecting suitable paths. We attempt to find the optimal balance between functional reuse and path length, maximizing the reuse degree of the path while ensuring link reliability. One possible approach to achieving this goal is to determine the maximum value of transmission hops based on link reliability requirements. By setting an appropriate reliability threshold, we can balance link reliability and reuse degree based on the length of the links. In this way, we can control the link length (u_k') to meet the link's reliability requirements as much as possible while improving the reuse degree of the path.

In conclusion, the link reliability mapping model based on functional reuse plays a crucial role in the joint optimization process of function deployment and bandwidth requirements. By setting the maximum value of transmission hops and controlling the link length, we can find the path with the highest degree of reuse while meeting link reliability requirements. This will provide significant improvements and optimizations in network reliability, bandwidth utilization, and service quality. Additionally, we believe that this model will provide valuable guidance for network management and resource scheduling, ensuring better reliability and performance of the network.

4. Algorithm Description and Analysis

4.1 Deep Reinforcement Learning Based Algorithm for Reliable Mapping of Service Function Chains

Deep reinforcement learning (as shown in Figure 2) is the application of deep learning's strong perceptual capabilities to the decision-making process of reinforcement learning, seeking the optimal policy by maximizing cumulative rewards. In this paper, deep reinforcement learning is applied to the reliable mapping problem of service function chains in the SDN/NFV architecture (WAN K, GAO X, HU Z, et al., 2020). GS-O is used to collect, analyze, and execute mapping strategies based on business information. However, due to the unknown VNF sharing degree, continuous interaction with the virtual and underlying layers is required to explore the environment, identify suitable VNF reliability requirements, and obtain the best deployment solution.

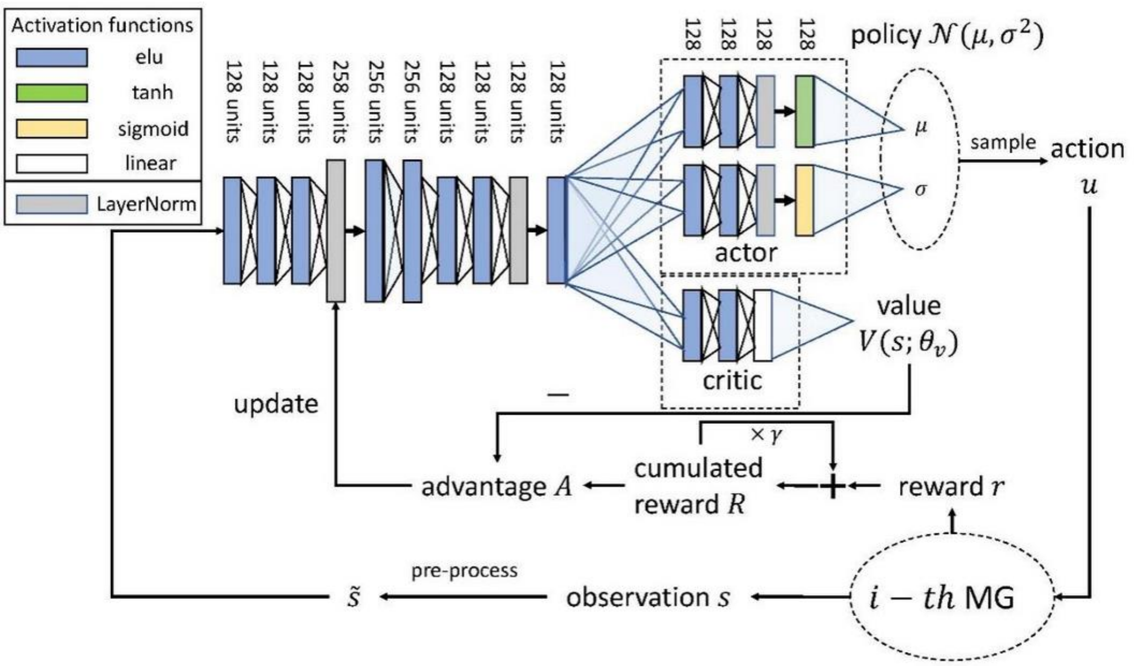

Figure 2. Deep reinforcement learning algorithm network structure

The defined state space is st = {Bleft, Cleft, bmap, Cmap}. Here, Bleft and Cleft represent the sets of remaining node resources and link resources, respectively, representing the state of the underlying layer. Bmap and Cmap are the sets of mapped components in the service function chain, representing the corresponding virtual network state. The node state includes the deployed node results and the degree of sharing, while the link state represents the deployed links. The action space is defined as at = {an, al, ao}, where an represents the node mapping action, al represents the link mapping action, and ao represents the resource allocation action (Zou X, Yang R, Yin C, et al., 2019). During the deployment process, if the selected physical node already hosts the VNF, the VNF can be reused, and the weight values can be recalculated. If the node does not host the VNF, computational resources need to be consumed to instantiate the VNF. To avoid learning from invalid action states, the action space can be filtered based on certain criteria, including path length limitation, resource limitation, and reliability limitation, resulting in a subset as shown in Formula (6).

$$\begin{aligned} N'_{kn_i} &= \{n_i \mid hop(s_k, n_{i-1}) + hop(n_{i-1}, n_i) \\ &+ hop(n_i, d_k) \le u'_k, R_{n_i} \ge (R_N^k)^{\omega_I}, \\ &c_{n_I}^k < c_i\} \cdot P_{S_k, n_{i-1}} \in P_{S_k, v_{I-1}^k}, P_{n_{i-1}, n_i} \\ &= \ell_{n_{i-1}, n_i}, P_{n_i, d_k} = \ell_{n_i, d_k}, n_i \in h(v_I^k) \end{aligned} \tag{6}$$

In this paper, a convolutional neural network (CNN) is used to approximate the Q-value function. Vectors [st, at, rt, st+1] are obtained through exploration of the environment and stored into the experience replay pool. Then, a random set of vectors is selected for training, allowing the neural network to accurately estimate the Q-values. Since the initial neural network may not provide correct Q-value estimates, the parameters of the network are adjusted using the immediate rewards generated by the immediate actions and the Q-values of the next state that reflect long-term rewards. To prevent overestimation of Q-values, two identical neural networks are used to separately estimate the current Q-values and the Q-values of the next state. The network estimating the current Q-values is referred to as the main neural network, while the network estimating the Q-values of the next state is called the target neural network.

The service function chain reliable mapping algorithm based on deep reinforcement learning can find the optimal deployment strategy in complex network environments by learning and optimizing the Q-value function. By exploring the state space and selecting appropriate actions, we can maximize the function reuse while ensuring link reliability, optimize resource utilization, and meet bandwidth requirements. The application of this algorithm will help improve the performance and reliability of service function chains, as well as enhance the efficiency and user experience of the entire network.

In summary, the service function chain reliable mapping algorithm based on deep reinforcement learning combines the perception ability of deep learning with the decision-making process of reinforcement learning. It seeks the optimal deployment strategy by maximizing cumulative rewards. By fitting the Q-value function and exploring the state space, we can achieve maximum function reuse, optimize resource utilization while ensuring link reliability, and meet bandwidth requirements. The application of this algorithm will help improve network performance and user experience, further promoting the development and application of SDN/NFV architecture.

4.2 Node Backup Algorithm Based on Functional Importance of Virtual Networks

When the reliability of the Virtual Network Function (VNF) is in high demand and there is no node that has been selected N'_{kn_i} is empty, we can use a backup-based approach to improve the reliability of the nodes. This is done by selecting two nodes for deployment, one of which is used as a backup node.

The node backup algorithm based on the importance of virtual network functions (VNFs) fully considers the importance of VNFs and enhances the redundancy and fault tolerance of nodes by introducing backup nodes to ensure service reliability in case of node failures.

During the node selection process, we need to consider the importance of each node and determine the backup node based on the reliability requirements of the VNF. By simultaneously selecting two nodes and designating one node as the backup, we can quickly switch to the backup node to ensure service continuity and availability, thus reducing the risk of service interruptions in case of node failures.

The node backup algorithm based on the importance of virtual network functions provides a flexible solution, particularly suitable for scenarios with high reliability requirements. By considering the importance of functions and the selection of backup nodes, we can effectively improve the reliability of nodes. The application of this algorithm can guarantee reliable network services even in the event of failures, avoiding business interruptions and service unavailability (Zhu J, Wu F & Zhao J., 2021).

In summary, the node backup algorithm based on the importance of virtual network functions enhances the reliability of VNFs by selecting two nodes and introducing a backup node. In situations where VNF reliability is high and no selected node is available, the backup mechanism of nodes ensures fast switching and continuous service availability. The application of this algorithm provides a feasible solution to ensure the reliability of network services and helps enhance user experience and satisfaction.

5. Simulation Experiments and Performance Analysis

This paper designs a series of simulation scenarios to evaluate the performance of the proposed algorithm. The underlying network consists of 50 physical nodes and several links, where the CPU and link bandwidth resources of nodes are randomly distributed within the range of [40, 90]. The number of virtual nodes in each Service Function Chain (SFC) is uniformly distributed within the range of [4, 7], and the CPU and bandwidth requirements of virtual nodes are uniformly distributed within the range of 1 to 15. Additionally, 10 types of VNFs are set, and the importance of each type of VNF is randomly generated within the range of 1 to 5.

We compare the request acceptance rates of three different methods through simulation experiments. As shown in Figure 3, a total of 5000 time units of simulation were executed, generating approximately 500 virtual network requests. The DQN-RDA algorithm takes into account the distribution of resources in the underlying environment and deploys based on the principles of resource load balancing and minimizing reliability waste. Compared to the CCI-RA and PARD methods, DQN-RDA considers more comprehensive factors. Therefore, it achieves a higher request acceptance rate, maintaining it at around 90%.

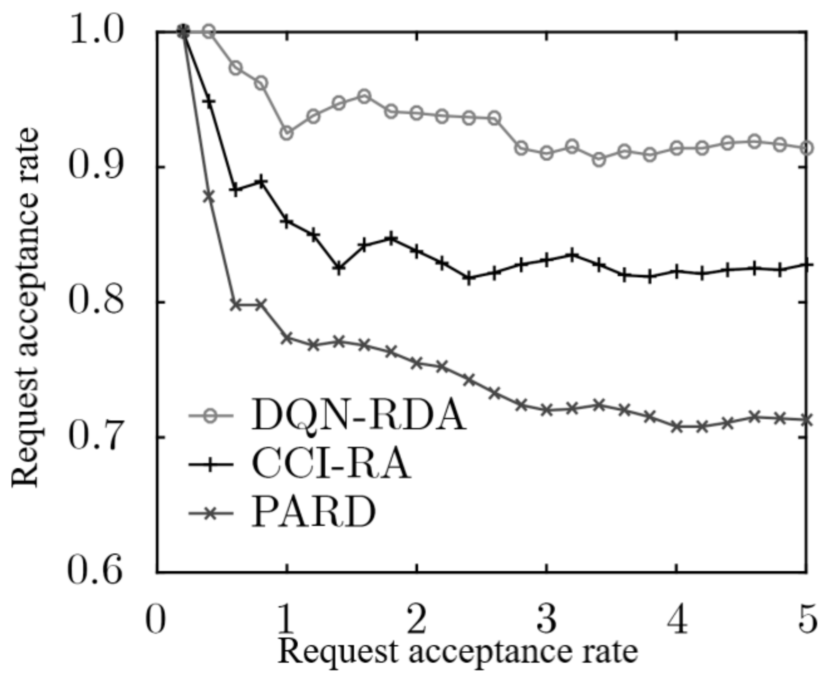

Figure 3. Comparison of SFC request acceptance rates

In order to evaluate the backup effectiveness of each algorithm under different reliability requirements, the SFC containing seven virtual nodes is used for validation. As shown in Figure 4, DQN-RDA consumes the least number of backup nodes. It firstly considers to fulfill the reliability requirements as directly as possible during the deployment process and secondly reduces the resource consumption by sharing the backups (Yong-Qiong Zhu, Ye-Ming Cai & Fan Zhang, 2022).

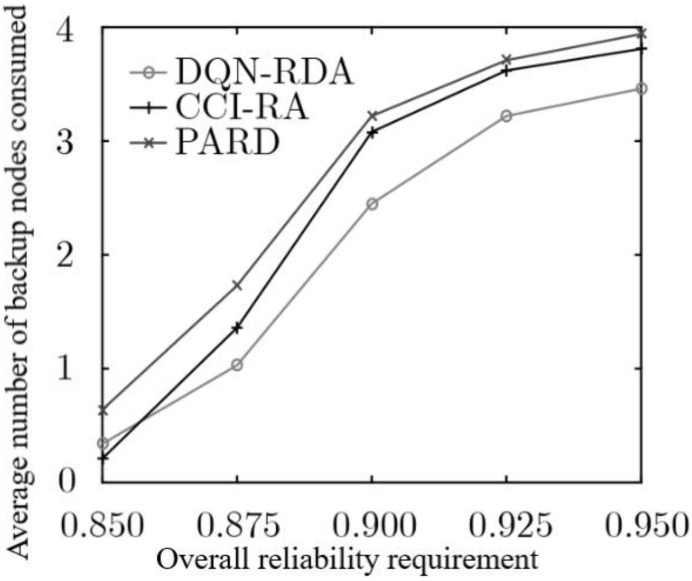

Figure 4.

By deploying the same set of SFCs in the underlying network and simulating the failure of physical nodes based on the probability of reliability failure, the impact of different algorithms on the failure of physical nodes is validated. As shown in Figure 5, the DQN-RDA method can minimize the impact of failures to the greatest extent.

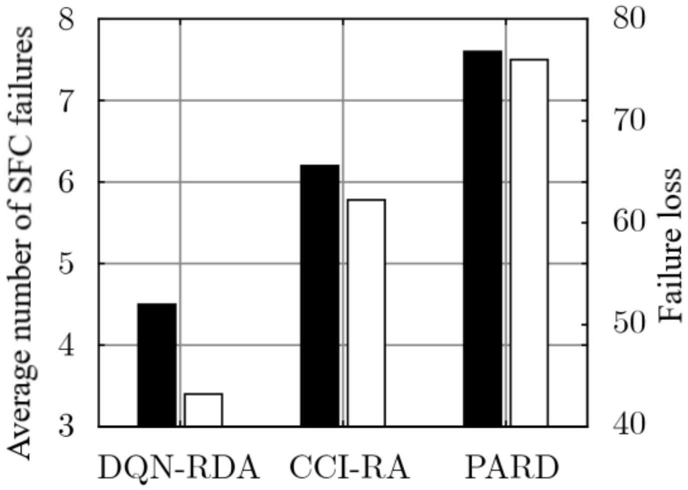

Figure 5. Comparison of SFC Failure Losses

Finally, the impact of learning efficiency on convergence effectiveness in deep reinforcement learning is verified by adjusting the learning rate. As shown in Figure 6, as the learning rate decreases, the convergence rate decreases, but the amplitude of oscillations after convergence becomes smaller and more stable. Higher learning rates lead to larger updates in Q-values and faster parameter updates, but they also result in greater fluctuations in parameter values, making it difficult to converge to a relatively stable value. Therefore, it is necessary to set an appropriate learning rate based on practical requirements.

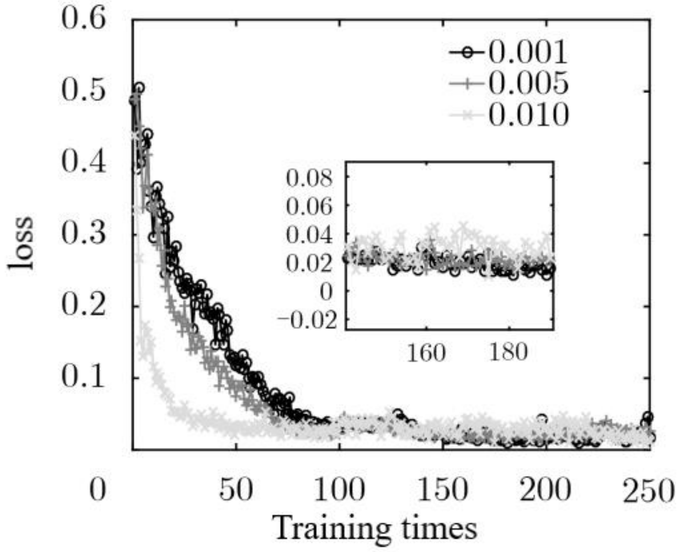

Figure 6. Effect of learning rate on convergence effect

In summary, through simulation experiments and performance analysis, we verify the effectiveness and reliability of the proposed algorithm. Under different simulation scenarios, the DQN-RDA algorithm shows better performance in terms of request acceptance rate, backup effect and failure impact. These experimental results are of great significance to further promote the research in network function virtualization and reliability optimization (Xi S, Xiaoqin Z, Yong Y, et al., 2022).

6. Conclusion

This paper addresses the reliability issue in traditional SFC deployment algorithms by studying a reliable deployment algorithm based on deep reinforcement learning. Experimental results demonstrate that the proposed algorithm effectively improves the reliability and performance of SFCs, thus having significant practical implications for network service deployment. Future research can further explore improvements and extensions to SFC reliable deployment algorithms. Additional factors and constraints, such as network topology changes and link failures, can be considered to comprehensively address challenges in practical deployments. Additionally, comparisons and integrations with other optimization algorithms can be conducted to further enhance the reliability and performance of SFCs. In summary, this research provides a new approach to reliable SFC deployment, achieving positive results in improving network service quality. We believe that through continued efforts and further research, SFC reliable deployment algorithms will offer broader prospects for the development and innovation of network technologies.

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