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Network Function Parallelization for High Reliability and Low Latency Services

JIANHONG ZHOU1,2, (Member, IEEE), GANG FENG2, (Senior Member, IEEE), AND YI GAO2, (Member, IEEE)



* School of Computer and Software Engineering, Xihua University, Chengdu 610000, China
* National Key Laboratory of Science and Technology on Communications, University of Electronic Science and Technology of China, Chengdu 610000, China

Corresponding author: Gang Feng (fenggang@uestc.edu.cn)

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 **ABSTRACT** In 5G-and-beyond wireless communication systems, Network Function Virtualization (NFV)has been widely acknowledged as an important network architecture solution to meet diverse service requirements in various scenarios. However, with the increase of network functions, the introduction of NFV may signi cantly increase the delay of traf c ows, which is much undesired, especially for Ultra Reliable and Low Latency Communication (URLLC) service. Network Function Parallelism (NFP) architecture has been recently proposed as an effective technique to address the bottleneck of NFV technology. NFP can potentially improve the reliability and reduce the delay of service function chains (SFCs). In this paper, we propose a learning based SFC deployment strategy under NFP architecture with aim to improve the service reliability while reducing the end-to-end service delay. Speci cally, service reliability is improved by deploying back-up virtual network function (VNF) nodes, while the ow delay is reduced via parallel network function processing. We formulate the VNF deployment as an integer-programming problem with objective of minimizing the reserved computing and bandwidth resources, while guaranteeing the service reliability and end-to-end delay. Considering the hardness and properties of the problem, we transform it as a Markov Decision Process (MDP), and employ a reinforcement-learning algorithm to solve it. We conduct simulations and the numerical results demonstrate that the proposed strategy can signi cantly improve the service reliability and delay performance, which are crucial for URLLC service.



 **INDEX TERMS** URLLC, NFV, NFP, parallel network service function chain.



**I. INTRODUCTION**

As one of the three major application scenarios of 5G mobile communication networks, Ultra Reliable and Low Latency Communication (URLLC) service is essential for a wide range of delay-sensitive applications, such as autonomous or assisted driving, augmented reality (AR), virtual reality (VR), tactile Internet, and industrial control. Although net-work service operators try to support such applications by using existing mobile communication systems, they cannot meet more stringent requirements, such as lower latency, higher reliability and security, of emerging applications. The requirements of some applications in terms of end-to-end delay and reliability are even lower than 1ms and higher than 99.9% respectively [1]. For example, remote surgery requires

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extremely high sensitivity and accuracy for object manipu-lation, and the round-trip data transport time is required to be lower than 1ms. Autonomous vehicles need to coordinate with each other to queue and overtake, and thus the reliability of message exchange should be higher than 99.9%. In current deployed LTE networks, the end-to-end delay is approxi-mately 50-100ms, which is about an order of magnitude higher than that of 5G [2]. Therefore, achieving low latency and high reliability requires improvement from the network architecture.

In recent years, Software De ned Network (SDN), Net-work Function Virtualization (NFV), and Mobile Edge Com-puting (MEC) have been recognized as three key architectural technologies for 5G. NFV is considered as the main entity of the 5G core network, in which the vendors implement network functions in Virtual Network Function (VNF) com-ponents, and VNFs are deployed on high-capacity servers

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J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

or basic cloud architecture instead of dedicated hardware, thereby reducing costs and improving system exibility. The provisioning of a service requires the execution of a set of VNFs, which in turn form a virtual Service Func-tion Chain (SFC). NFV eliminates the dependence on the hardware platform, and can improve throughput and cost ef ciency by exibly deploying network functions. Mean-while, using mobile edge computing and deploying the VNFs on the edge network can effectively reduce service delay [3]. However, the latency requirements of URLLC are still very challenging in SDN/NFV based mobile networks. While research on parallel computing in computer program-ming and high-performance computing has become relatively mature, NF parallelism has just been recently proposed to improve NFV performance [4]. This kind of SFC supporting network function parallelism is called a parallel network service function chain [4]. Therefore, the rational deployment of parallel network function service chains in NFV can enable multiple independent network functions of service requests to work in parallel, thus shortening the effective length of SFC, and signi cantly reducing the delay.

On the other hand, URLLC service requires not only extremely low latency, but also high reliability. Under the NFV-based network architecture, SFC service requests usu-ally involve multiple VNFs. Therefore, end-to-end service reliability is not only determined by a single node, but also by all VNFs of the serving SFC. Any failure of one VNF of the SFC will cause the service to be interrupted, resulting in wasted resources and service interruptions. Thus, ensur-ing end-to-end reliability of SFCs is critical for providing URLLC services. Redundancy is an effective method to improve reliability [5], [6]. When a VNF node malfunctions, the carried traf c may be re-routed to the backup node to achieve fault recovery by reserving backup VNF and band-width resources. Intuitively, the more redundant backups, the higher the service reliability. However, this mechanism may increase the routing length and thus the end-to-end delay accordingly. Therefore, it is imperative to develop ef cient SFC backup scheme by considering delay and reliability simultaneously. Obviously, after introducing the network function parallelization, redundant backup design is different from that in traditional NFV based networks. When VNFs executed in parallel are deployed on different physical hosts, there are multiple parallel links. Thus, the failure of a phys-ical host implementing VNFs may cause some links failure instead of all. This may cause a chain reaction as many pack-ets cannot be merged. Therefore more attention should be paid to the reliability of the parallel service function chains.

At present, the research on reliability for URLLC service mainly focuses on sequential SFCs. Through the deployment of highly reliable nodes and redundant backups of SFCs, the reliability can be effectively improved [5] [9]. In [7], in order to ensure the end-to-end reliability of SFC, a priority-based deployment scheme was proposed. VNFs with different priorities are deployed on hosts with different reliability. To improve the overall reliability, VNFs with higher priorities

VOLUME 8, 2020

are deployed on physical hosts with higher reliability. The authors of [8] proposed a joint optimization framework called recon gurable awareness and latency-limited service chain for sequential SFC. This framework combines itera-tive backup selection and routing processes, and allocates resources to the network serving host as much as possible to ensure high reliability and low latency. The authors of [5] proposed an ef cient backup method, CERA, by selecting suf cient backup VNFs to meet the reliability requirement of services. In view of the shortage of traditional redundant backups, the authors of [6] proposed an ef cient redundant backup algorithm GREP, which can guarantee the reliabil-ity of the service within the polynomial time complexity and reduce the backup cost. The authors of [9] proposed to model the procedure of determining the required number of VNF backups as an incremental problem, and proposed a heuristic algorithm to solve it. Unfortunately, all of the aforementioned research work is mainly focused on sequen-tial SFC, which is far from adequate for meeting the delay and reliability requirement of URLLC service. Intuitively, recently emerging Network Function Parallelism (NFP) [4] can potentially improve both service reliability and delay performance. In [10], we propose a new joint Two-Tier NF Parallelization (TNP) framework, which can agilely and ex-ibly organize parallel NF processing to greatly improve SFC performance in terms of latency and throughput. But the reliability aspect is not taken into account.

In this paper, with aim to minimize reserved resources under the premise of meeting end-to-end reliability and delay constraints under NFP architecture, we propose an intelligent VNF backup node deployment strategy for parallel SFC. Based on the properties of NFP, an MDP model is formulated, and a backup scheme using Q-learning framework is pro-posed. We evaluate the performance of our proposed backup mechanism using simulation experiments. Numerical results show that the proposed learning based backup algorithm can achieve higher network throughput on the premise of meeting the reliability and delay requirements, compared with ‘‘The parallel SFC based Q-learning (QL-P)’’, ‘‘lowest reliability rst (LRF)’’, ‘‘minimum computing resource rst (MCRF)’’, ‘‘Random backup’’ and ‘‘sequential SFC-based Q-learning (QL-S)’’ algorithms. The remainder of the paper is orga-nized as follows. Section II describes the system model. In Section III, we describe the high-reliability SFC deploy-ment model under NFP architecture and formulate the opti-mal SFC deployment strategy problem. Next, we elaborate the reinforcement learning algorithm for solving the problem in Section IV. Section V presents numerical results as well as discussions. Finally, Section VI concludes this paper.

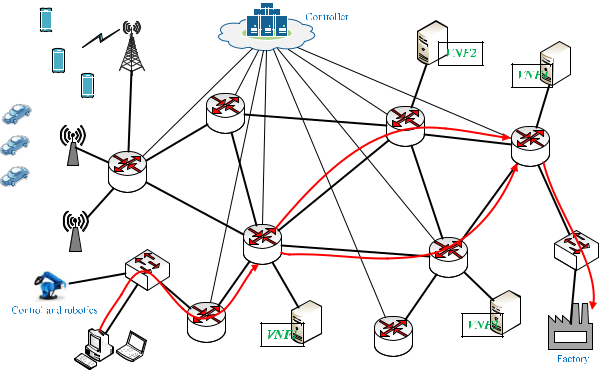
**II. SYSTEM MODEL**

In NFP architecture [4], network functions could be executed in parallel in NFV network architecture. Fig.1 shows a paral-lel SFC model. Each service request can be accomplished by a set of VNFs, and a virtual SFC composed of multiple VNFs is formed in accordance with the execution order. When a

75895

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

**FIGURE 1.** Parallel SFC model.



service request reaches the ingress network element of the core network, the corresponding SDN controller deploys cor-responding VNFs on physical nodes and arrange the execu-tion order for all VNFs of the SFC according to every VNF’s requirements on computing resources, bandwidth resources, storage resources *etc.*. A physical link in the network with bandwidth resources is used for data packet transmission and a physical node with computing and storage resources performs corresponding VNF. In this paper, we assume that every physical node is able to execute every VNF. The phys-ical node will process, forward, copy, and merge the data packets according to the instructions of the controller, and nally transmit the data packets to the destination node.

We assume that each SFC in the network corresponds to a service request. The network elements for all data packets entering and exiting the network are known and xed. The VNFs required for all data packets execution of one request are the same [4]. NFP compilers are responsible for the parallelized deployment of each SFC, which is called parallel SFC. Speci cally, the NFP compiler rst identi es the VNFs that can be executed in parallel, and then constructs a parallel service function structure. In the example of Fig. 1, the dashed curve represents a deployed parallel SFC. As *VNF*2 and *VNF*3 can be executed in parallel, after executing *VNF*1, the data packets are copied into two copies and forwarded to traverse different paths, and the merge is completed before *VNF*4 is executed.

The physical network of Fig. 1 can be represented as an undirected graph *G* .*V* ; *E*/, where *V* and *E* represent the physical nodes set and link set respectively. For any physical link *e* 2 *E*, the bandwidth and transmission delay are denoted by *Be* > 0 and *Te* > 0 respectively. For physical node

* 2 *V* , the computing resource is denoted by *Cv* > 0. A set of VNFs deployed on any physical, *etc.*). Thus, each node has a reliability level, and all the VNFs running on the node inherits the reliability level of this node. Assume that the failure probability of each node is independent of each other, and only the failure of the physical node is considered here, and the failure of other network components, such as routers, switches, bridges, *etc.*, is not considered. To improve

75896

the reliability, some VNFs will be backed up. When a physical node fails, the backup VNFs running on other physical nodes are executed instead of the working VNFs deployed on the failure node. The node where the backup VNF is deployed should be connected to the predecessor and successor nodes of the failure node. We call the connections between backup node and the predecessor or successor node as backup links. Apparently, the backup links and backup node should reserve adequate bandwidth resources and computing resources for the backup VNF.

Let the set of all service requests be *S*. After NFP com-pilation of all parallel SFCs, the deployment scheme can

|  |  |  |  |
| --- | --- | --- | --- |
| be represented as a directed subgraph *Gi* *Vi*; *Ei*; | *i* | of |  |
| *req* |  |

the physical network *G* .*V* ; *E*/,where *Vi* D f*v*1*i*; : : : ; *v*j*iFi*jg represents the set of physical nodes used to deploy the VNFs of the parallel SFC *i* and *Fi* is the VNF set of parallel SFC *i*. *Ei*

and *reqi* represent the set of links that link all the nodes and the reliability requirement for the parallel SFC *i*, respectively.

For simplicity, we assume that the bandwidth requirement of the SFC remains unchanged, which is equal to the initial

bandwidth *bireq*. Let *cireq*;*j* represent the computing resources required for the backup VNF *j* 2 *Fi* of the parallel SFC *i*.

**III. PROBLEM FORMULATION**

**A. HIGH-RELIABILITY DEDICATED BACKUP MODELING**

|  |  |  |
| --- | --- | --- |
| Assume that the required reliability for any SFC *i* is | *i* | (0 < |
|  | *req* |  |

*reqi* < 1), and the required bandwidth is *bireq* > 0. The VNF set of the SFC *i* is *Fi* *F*. The ingress and egress network elements are *i* and *i* respectively. The reliability of any node

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| deploying VNF *j*; 8*j* 2 *Fi* can be expressed asV | | |  |  |
| *rj* D | *MTBFj* | ; | (1) |  |
| *MTBFj* C *MTT Rj* |  |

where *MTBFj* and *MTT Rj* represent the mean time between failures and the mean time to repair the physical node deploy-ing the VNF *j*, respectively. Obviously, 0 < *rj* < 1. It has mentioned in [11] that to avoid load imbalances and improve reliability, any non-parallel VNFs cannot be deployed on the same node. Meanwhile, for a service to work properly, all involved VNFs need to be executed appropriately. In other words, all the nodes deploying all VNFs of the same SFC should work properly.

Thus, for sequential SFCs, we assume that any two VNFs cannot be deployed at the same physical node, and the service reliability can be expressed as

|  |  |  |
| --- | --- | --- |
| *F* |  |  |
| Y | (2) |  |
| 9 D *rj*: |  |

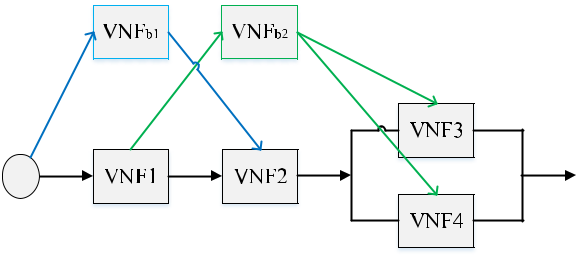
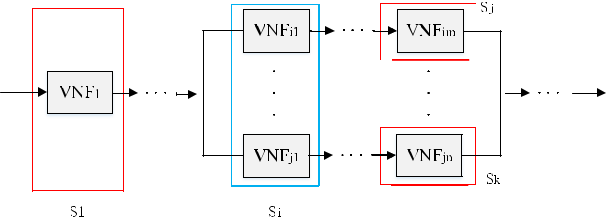
*j*D1

In the deployment of parallel SFC, multiple VNFs executed in parallel may be deployed on the same physical node. If a physical node with multiple VNFs fails, all VNFs deployed on this node will fail accordingly. Thus, the reliability calcu-lation is different from that for the traditional sequential SFC. Speci cally, the reliability of the parallel SFC is a product of the reliability of all mapped physical nodes. Some reliability

VOLUME 8, 2020

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

**FIGURE 2.** Illustration of the SFC parallel execution.



**FIGURE 3.** Dedicated backup model for parallel SFC.

calculation methods of parallel network functions are given in references [7] and [10]. As shown in Fig.2, a parallel SFC is divided into different subsystems according to different nodes. Each subsystem may deploy multiple VNFs. Let a par-

allel SFC consists of ( 1)subsystems Q ; : : : ; ,

*K K* *S* D f*s*1 *sk* g

|  |  |  |  |
| --- | --- | --- | --- |
| and each subsystem *sn* consists of *kn*; (*kn*1; | | *kn* D |  |
|  |  | SFC can |  |
| j*Fn*j)VNFs. In general, the reliability of the parallel P | | |  |
| be expressed asV | *K* |  |  |
|  |  |  |
| D | Y |  |  |
| Re(*sn*); | (3) |  |

*n*D1

where Re(*sn*); 0 < Re(*sn*) < 1 indicates the reliability of the physical node where the subsystem *n* is located. Obvi-ously, for the same request, *K* and *F* represent the number of multiplication factors when calculating the reliability for parallel and sequential VNF deployment respectively, and

* < *F*. It can be seen that when multiple VNFs deployed on the same physical node *n* can be executed in parallel, the reliability of the entire SFC can be improved to a certain extent.

There are generally two types of backup models, namely dedicated backup and shared backup [12]. In order to sup-port highly reliable services, we adopt the dedicated backup model. Fig. 3 shows a dedicated backup model with parallel network functions. The backup VNFs *VNFb*1 and *VNFb*2 pro-vide dedicated backup for working VNFs *VNF*1 and *VNF*2, respectively. Meanwhile, the required backup links are added between the backup nodes and their neighboring working nodes. Unlike traditional sequential SFC backup, a VNF mapping node may have multiple inbound and outbound ows. Therefore, when considering the selection of node for backup VNFs, it is necessary to choose the node with least backup links to reduce the reservation of backup bandwidth resources, and then lower the resource occupation ratio to the

VOLUME 8, 2020

greatest extent. We de ne binary 0-1 variables *xiv*;*j*(*i* 2 *S*; *j* 2 *Fi*; *v* 2 *V* ) to represent the backup deployment of VNF *j* inthe SFC *i*, *i.e.*,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *xiv*;*j* D( | 1; | *VNF j of SFC i is deployed on node v* | : (4) |  |
| 0; | *otherwise* |  |

We de ne the binary 0-1 variable *yei*;*j*(*i* 2 *S*; *j* 2 *Fi*; *e* 2 *E*) to represent the link occupied by VNF *j* in the SFC *i*,which means that the link *e* is occupied to execute the packet transmission which is served by the VNF *j* of SFC *i*.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *yie*;*j* D( | 1; | *link e occupied by VNF j of SFC i* | : (5) |  |
| 0; | *otherwise* |  |

The binary 0-1 variable *hi*;*j*(*i* 2 *S*; *j* 2 *Fi*) is introduced to indicate whether the VNF *j* of the SFC *i* is backed up, and we de ne

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| *hi*;*j* D( | 1; | *VNF j of SFC i is backed up* | : | (6) |  |
| 0; | *otherwise* |  |

* 1. **HIGH-RELIABILITY DEDICATED BACKUP MODELING**

In our system, the highly reliable backup of services is considered in a resource limited environment. Thus, when selecting backup nodes, it is necessary to jointly consider node computing resource, reliability, link resource and link delay limits.

1. NODE CONSTRAINTS

As a failure of the physical node will cause all VNFs deployed on the node to fail, all the nodes deploying working VNFs are inappropriate to serve as backup nodes. Meanwhile, to save resources, we only consider the case of a maximum of one backup copy. The node constraints are given as followsV

|  |  |  |  |
| --- | --- | --- | --- |
| *xik*;*j* D0; | 8*i* 2 *S*; | 8*j* 2 *Fi*; 8*k* 2 *Vi*; | (7) |
| X *xik*;*j* 61; | 8*i* 2 *S*; | 8*j* 2 *Fi*: | (8) |
| *k*2*V* |  |  |  |

When a VNF is deployed on a physical node, the physical node needs to reserve computing resources for executing this VNF. Assume the actual computing resource of node *k* is *Ck* , another node constraint is

X X

|  |  |
| --- | --- |
| *xik*;*j creqi*;*j* 6 *Ck* ;8*k* 2 *V* : | (9) |

*i*2*S j*2*Fi*

To improve the reliability of the SFC with parallel network functions, multiple backup VNFs may be backed up on the same node, and two VNFs that cannot be executed in par-allel cannot be backed up on the same node. We de ne the 0-1 variable *zif* ;*f* 0 . If and only if *zif* ;*f* 0 D 1, the VNF *f* and *f* 0 of SFC *i* can be executed in parallel, and not vice versa. Thus, there’re one more node constrain as

*xik*;*f* C*xik*;*f* 061C*zif* ;*f* 0; 8*i* 2 *S*; 8*f* ; *f* 0 2 *Fi*; 8*k* 2 *V* : (10)

Assume there are *n* VNFs of an SFC are deployed on the same physical node, of which *m*(*m* < *n*) VNFs are

75897

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

backed up VNFs. When the working node fails, the service cannot be provisioned normally. In this case, the backup only cause waste of resources rather than improving end-to-end reliability. Thus, all VNFs deployed on the same working node can only be backed up VNFs or working VNFs. For two different network functions deployed on the same node, the following constraint must be metV

*xiu*;*f xiv*;*f* 0D0; 8*i* 2 *S*; 8*f* ; *f* 0 2 *Fi*; 8*u*; *v* 2 *V* : (11)

2) TRAFFIC CONSTRAINTS

For 8*e* 2 *E*, the sum of the reserved bandwidth of all backup links mapping to *e* cannot exceed the maximum bandwidth provided. We thus have the following constraintV

X X

|  |  |
| --- | --- |
| *yie*;*j breqi* 6 *Be*;8*e* 2 *E*: | (12) |

*i*2*S j*2*Fi*

Due to the involvement of backup, the traf c of working VNF nodes will no longer be conserved, and the traf c conservation constraints cannot be used. We call the physi-cal node where the previous VNF of current working VNF resides as the predecessor node, and the physical node where the next VNF of current working VNF resides as the suc-cessor node. A backup VNF node in *Gi* may have multiple predecessors and successors. Assume that the set of prede-

cessor nodes of the backup VNF *j* 2 *Fi* of the SFC *i* is *ViF*;*j*(*ViF*;*j* 2 *Vi*) and the set of successor nodes is *ViL*;*j*(*ViL*;*j* 2 *Vi*).If the predecessor (successor) of the backed up VNF *j* is

the ingress network element (egress network element), then *ViF*;*j* D *i*;(*ViL*;*j* D *i*). In this case, these nodes should meetthe following constraints instead of the traf c conservation constraintsV

X

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  |  | *yil*;*j* D *hi*;*j*; | 8*i* 2 *S*; 8*j* 2 *Fi*; 8*vm* 2 *ViF*;*j* |  |
| *l*:*head*D*vm* | | | | *L* |  |
|  | X | | *l*0 |  |
| *l*0 | *yi*;*j* D *hi*;*j*; | 8*i* 2 *S*; 8*j* 2 *Fi*; 8*vn* 2 *Vi*;*j*: (13) |  |
|  | D |  |
| :*tail* | *vn* |  |  |
|  |  |  |

The node where the backup VNF is located on no longer meets the traf c conservation, and the in ow and out ow are as the same as the working VNF node. The in ow and out ow of the backup node is j*ViL*;*j*j and j*ViF*;*j*j, respectively. Thus following constraints should be satis edV

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| *l* | XD | *yil*;*j* | D *xiv*;*j* j*ViL*;*j*j; | 8*i* 2 *S*; *j* 2 *Fi*; 8*v* 2 *V* |  |
| *xiv*;*j* |  |  |
|  | :*head v* | |  |  |  |
| *xiv*;*j* | X | *yil*;*j* D *xiv*;*j* j*ViF*;*j*j; | | 8*i* 2 *S*; *j* 2 *Fi*; 8*v* 2 *V* : |  |
|  |  |

*l*:*tail*D*v*

(14)

If the working link is a serial link, that is j*ViL*;*j*j D j*ViF*;*j*j D 1,

|  |  |  |  |
| --- | --- | --- | --- |
| P | *yil*;*j* D | P |  |
| then | *yil*;*j*, which satis es the traf c con- |  |
| *l*:*head*D*v* |  | *l*:*tail*D*v* |  |

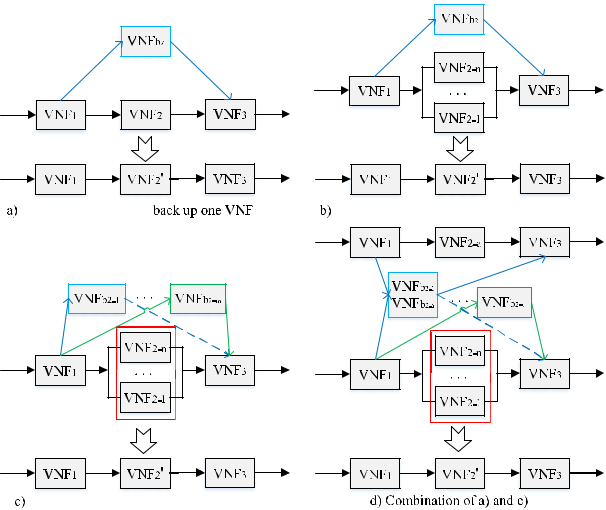
servation. For the other nodes meeting the traf c conservation should satisfy the following constraintV

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| XD | *yil*;*j* | D | X |  |
|  | *yil*;*j*; |  |
| *l*:*head v* | |  | *l*:*tail*D*v* |  |

(8*i* 2 *S*; *j* 2 *Fi*; 8*v* 2 *V* *ViF*;*j ViL*;*j*; *xiv*;*j* D0): (15)

75898

**FIGURE 4.** Backup SFC update model.



3) RELIABILITY CONSTRAINTS

In sequential SFC backup, it is only necessary to consider the constraint that the backup of different VNFs cannot be placed on the same node, and thus the backup design for reliability is easy. In parallel SFC backup, multiple VNFs can be deployed on the same physical node to execute in parallel. Meanwhile, multiple VNFs can also be divided into multiple branches to execute concurrently and then the results are merged. In this case, the backup design for reliability becomes much more complicated. To address this dif culty, we continuously update the parallel SFC structure by com-bining working VNFs and backup VNFs into new VNFs. As shown in Fig 4, several possible situations for backing up VNFs in the NFP architecture are listed.

As mentioned above, at most one copy is backed up for VNF *j* of SFC *i*. If only one backup VNF is deployed on the physical node, the model can be illustrated in Fig 4 (a). The reliability after backup isV

|  |  |
| --- | --- |
| 2 D 1 (1 *r*2) (1 *rb*2); | (16) |

where *r*2; *rb*2 represent the reliability of the physical node where *VNF*2 and *VNFb*2 are deployed, and 2 is the reliability of the combined new VNF. As shown in Fig 4(b), if several backup VNFs deployed on one physical node are executed in parallel, while the corresponding working VNFs are deployed on several physical nodes, the reliability after backup isV

|  |  |  |  |
| --- | --- | --- | --- |
|  | *n* |  |  |
| 2 D 1 (1 *rb*2) (1 | Y |  |  |
| *r*2 *i*): | (17) |  |

*i*D1

It is obvious that the reliability of the backed up VNFs is higher than that of the same VNFs without backup. The higher the reliability of the node with backup VNF is, the greater the reliability of the backed up VNF is. Mean-while, backup on the same physical node can reduce opera-tion and maintenance costs.

VOLUME 8, 2020

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Next, we consider that *n* working VNFs are deployed on | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | the selection of backup nodes, the change of link delay also | | | | | | | | | | | | | | | | | | | | | | | | |  |
| one node as shown in Fig 4(c). In this case, all the backup | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | needs to be considered. | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| VNFs may be backed up on the same node or on different | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | Different service function structures have different end- | | | | | | | | | | | | | | | | | | | | | | | | |  |
| physical nodes. Let *n* working VNFs be backed up on *m*(*m* 6 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | to-end delay calculation methods. For description simplicity, | | | | | | | | | | | | | | | | | | | | | | | | |  |
| *n*) physical nodes and the reliability of the updated *VNF*2isV | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | we de ne network function delay 1 as the delay required to | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | *m* | |  |  |  |  |  |  |  |  |  |  |  |  |  | execute a VNF, including the link delay of routing to the VNF | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  |  | 2 D 1 | | |  | (1 | | |  |  | *r*2) (1 | | | | | |  |  |  |  | *rb*2 | *i*); | |  |  |  |  |  |  | (18) | | | node and the processing delay performed by the VNF, Then | | | | | | | | | | | | | | | | | | | | | | | | |  |
| *i*D1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |  |
| Y | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | 0 |  | | | | | | | | |  |
| where *r*2 | | and *rb*2 *i* | | | |  | represent the reliability of the physical | | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| node on which the *n* VNFs are deployed and the reliability of | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  |  | 1 D max(E*tL* ) C *t*N*P* C max( *t* *L* ); | | | | | | | | | | |  |  |  |  | (21) | | | | |  |
| the *ith* backup node, respectively. Obviously, the reliability of | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | where E*tL* is the maximum link delay from the previous VNF | | | | | | | | | | | | | | | | | | | | | | | | |  |
| the updated *VNF*2 after backup is enhanced. | | | | | | | | | | | | | | | | | | | | | | | | considered | | | | | | | | | as | mapping node to the current VNF mapping node; *t*N*P* is the | | | | | | | | | | | | | | | | | | | | | | | | |  |
| At last, | | | a more | | |  | complicated | | | | | | | | | | situation | | | | | | is | processing time of current VNF; | | | | | | | | | | | | | 0 | is the maximum link | | | | | | | | | | |  |
| shown | in | | Fig | 4(d). The | | | | | | | |  | working | | | | | |  | VNFs, | | | | *VNF*2 *a* and | | | | | | | | | | *t L* |  |
|  |  | delay from the current VNF mapping node to next VNF | | | | | | | | | | | | | | | | | | | | | | | | |  |
| *VNF*2 | 1 |  | *VNF*2 | |  | *n*, | | are executed in | | | | | | | | | | | | | parallel on different | | | | | | | | | | | | |  |
|  |  | mapping node. Thus, the actual requested network function | | | | | | | | | | | | | | | | | | | | | | | | |  |
| physical nodes, while the physical node with backup VNF | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |  |
| latency isV | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| *VNF*2 *a* also backs up other VNFs. We assume that the | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| backup node of *VNF*2 | | | | | | | |  | *a* is as the same as the backup node | | | | | | | | | | | | | | | | | | | | | | | | |  | *t* | *i* D |  |  |  |  | [1 | *i*;*j* | *h* | *i*;*j* C | 1 | 0(1 | *h* |  | )]; | 8 | *i* | 2 | *S*; | (22) | | | | |  |
| of *VNF*2 | | 1. Let the event *p*0 | | | | | | | | | | | indicate that the physical node, | | | | | | | | | | | | | | | | | | | | |  |  | *j*2*Fi* | | | |  |  |  | *i*;*j* |  | *i*;*j* |  |  |  |  |  |  |  |  |  |
| where *VNF*2 1-*VNF*2 | | | | | | | | *n* are deployed, is working normally, | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  | X | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| the event *p*00 indicate that the physical node, where *VNF*2 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | *a* | where 1*i*;*j* and 1*i*;*j*0 are the network function delay for backup | | | | | | | | | | | | | | | | | | | | | | | | |  |
| are deployed, is working normally, and the event *pi* | | | | | | | | | | | | | | | | | | | | | | | | | | | | indicate | | | | | | VNF *j* and working VNF *j* of SFC *i*, respectively. Meanwhile, | | | | | | | | | | | | | | | | | | | | | | | | |  |
| that the physical node, where *VNFb*2 | | | | | | | | | | | | | | | | | | | *i* are deployed, is work- | | | | | | | | | | | | | | | the average requested network function latency *t*N*i* D | | | | | | | | | | | | | | | | | | | |  |  | *ti* |  | ; |  |
|  | j | *Fi* | j |  |
| ing normally. Then the reliability of the updated VNF *VNF*2 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | 8*i* 2 *S*, which will be used in the next Sec. | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  |
| is |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | To quantify the delay incurred by the switching process | | | | | | | | | | | | | | | | | | | | | | | | |  |
| 2 D | | P(*p*0*p*00) | | C |  | P(*p*0*p*00) | | | | | |  | P(*p* | | |  | : : : *p* | | |  | ) | C | P(*p*0*p*00) | | | |  | P(*p* | | |  | ) |  | from working VNF node to the backup VNF node, we de ne | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  |  |  | N | |  |  |  |  |  | ) | 1 |  |  |  | *m* |  |  | N |  |  |  |  |  | 1 |  |  | the constraint factor as the tolerable delay increment fac- | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  | C | P(*p*0*p*00) | |  | | P(*p* | | 1 | : : : *p* | | | | *m* |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | tor. Thus, to avoid the delay increased too much, the delay | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  | N N |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| D | | P(*p*0*p*00) | |  |  | P(*p*0) | | | |  | P(*p* | | | 1 | : : : *p* | | | *m* | ) | C | | P(*p*0*p*00) | | |  | P(*p* | | | 1 | ) |  |  |  | constrain *t* | | | *i* | should satisfy | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | C N | | | | |  |  |  |  |  |  |  |  |  | N |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  | *m* | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | *ti* 6 | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| D *ra* *rb* C (1 | | | | | | |  | *ra*) | | | | |  |  | *ri* C *ra* (1 | | | | | | | | *rb*) (1 | | | | |  |  | *r*1) | | |  |  |  |  |  |  |  |  | 1*i*;*j*0; | | 8*i* 2 *S*; | | |  |  |  |  | (23) | | | | |  |
| *i*D1 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | *j* | | | | | | | | | | | | | | |  |
| > *ra* *rb*; | | | |  |  |  |  |  |  |  |  | Y | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | (19) | | |  |  |  |  |  |  |  |  |  |  | X | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | where |  | 1 | | |  |  | is the service delay of SFC *i* | | | | | | | | | before backing | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| where *ra* and *rb* represent the reliability of the physical node | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | up. |  | P*j* |  |  | *i*;*j* | 0 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| on which the *VNF*2 | | | | | |  | *a* is deployed and on which the *VNF*2 | | | | | | | | | | | | | | | | | | | | | | | | |  | 1- |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| *VNF*2 | *n* are deployed, respectively. In this case, the overall | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | **C. PROBLEM FORMULATION** | | | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |
| reliability of the updated VNF decreases with the number of | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |
| In the deployment of parallel SFC, there are a large number | | | | | | | | | | | | | | | | | | | | | | | | |  |
| backup hosts. | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| For each SFC *i*, there is a reliability requirement | | | | | | | | | | | | | | | | | | | | | | | | | | |  | *reqi*, and | | | | | | of VNFs that can be executed in parallel, and the reliability is | | | | | | | | | | | | | | | | | | | | | | | | |  |
| the links deployed on the physical network have a reliability | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | supposed to be higher than that of traditional sequential SFC | | | | | | | | | | | | | | | | | | | | | | | | |  |
| *i*. The new reliability after backup can be denoted by | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |  | *i*0. | deployment. However, there are still some low-reliability | | | | | | | | | | | | | | | | | | | | | | | | |  |
| Then the reliability needs to meet the constraintsV | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  | physical nodes, which affect the reliability of the entire | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  | link seriously. Fortunately, we could improve the reliability | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  |  | *i*0 | > | |  | *reqi*; | | |  |  | *i* | 0 > | | |  | *i*; |  |  | 8*i* 2 *S*: | | | |  |  |  |  |  |  |  | (20) | | | of these nodes through backup. Considering parallel SFC | | | | | | | | | | | | | | | | | | | | | | | | |  |
| 4) DELAY CONSTRAINT | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | backup in a known network, our goal is to obtain an optimized | | | | | | | | | | | | | | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | VNF backup scheme with the smallest resource occupation | | | | | | | | | | | | | | | | | | | | | | | | |  |
| Dedicated redundant backup will not change the deployed | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | under a speci c reliability constraint. To back up a VNF | | | | | | | | | | | | | | | | | | | | | | | | |  |
| structure of the parallel SFC. When a node fails, the working | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | on a physical node, it is necessary to reserve computing | | | | | | | | | | | | | | | | | | | | | | | | |  |
| VNF will be transferred to the backup VNF node for execu- | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | resources on the node as well as reserve bandwidth resources | | | | | | | | | | | | | | | | | | | | | | | | |  |
| tion. Assume that the execution time of the working VNF and | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | for certain links. Different VNFs require different resources. | | | | | | | | | | | | | | | | | | | | | | | | |  |
| the corresponding backup VNF are the same, the change in | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | Thus, the resources reserved for different backup VNFs are | | | | | | | | | | | | | | | | | | | | | | | | |  |
| the delay for executing the backup VNF instead of the work- | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | also different. Thus, the backup problem mentioned above | | | | | | | | | | | | | | | | | | | | | | | | |  |
| ing VNF is only the change in the link delay. If the backup | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | can be formulated as a 0-1 integer-programming problem. | | | | | | | | | | | | | | | | | | | | | | | | |  |
| VNF node is far from the working VNF node, it will cause | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | As minimizing bandwidth and computing resources are con- | | | | | | | | | | | | | | | | | | | | | | | | |  |
| a sharp increase in link delay. Therefore, when considering | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | sidered simultaneously, we can formulate our problem as a | | | | | | | | | | | | | | | | | | | | | | | | |  |
| VOLUME 8, 2020 | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 75899 | | | | |  |

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J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

multi-objective constrained optimization problem as

|  |  |  |
| --- | --- | --- |
|  | X X X | X X X |
| min( | *xik*;*j creqi*;*j*, | *yie*;*j breqi*):(24) |
|  | *i*2*S j*2*Fi k*2*V* | *i*2*S j*2*Fi m*2*E* |

Note that we did not present the constraints in (23) for brevity. A common method for solving multi-objective optimization problems is to transform the multi-objective optimization problem into a single-objective optimization problem through mathematical transformations, *e.g.* the evaluation function method. Then, an approximate optimal solution of the origi-nal problem can be obtained by solving the single-objective optimization problem. In this paper, we choose the weighted summation of the two objective functions after normalization as the evaluation function. The weighting factors are and

( C D 1). Then the objective function of the original problem can be transformed intoV

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  | |  | X X X | |  |  |
| min ( |  |  |  |  | | (*xik*;*j* *creqi*;*j*) | |  |
| P | | *Ck* |  |
|  |  |  | *i*2*S j*2*Fi k*2*V* | |  |  |
|  | *k* | *V* |  |  |  |  |
|  | 2 |  |  |  |  | X X X |  |  |
| C | |  |  | |  | (*yie*;*j* *breqi* | )) |  |
|  | *Be* | |  |
|  |  | P | |  |  | *i*2*S j*2*Fi e*2*E* |  |  |
|  |  | *e* | *E* |  |  |  |  |
|  |  | 2 |  |  |  |  |  |  |
| s:t: Constraints(6) (14); (19); (22): | | | | | | | (25) |  |

where (6) (10) are the node constraints, (11) (14) are the traf c constraints, (19) is the reliability constraint, and (22) is the delay constraint. Obviously, this is a typical 0-1 integer-programming (0-1 IP) problem with multi-constraints, and some traditional continuous region solutions are infeasible for this problem as our 0-1 IP problem is discrete. Cur-rently, there are three types of algorithms for solving such problems: precise algorithms (*i.e*. dynamic programming, recursive method, retrospective method, branch-and-bound method, *etc*.), approximation algorithms (*i.e*. greedy algo-rithm, Lagrange algorithm, *etc*.), and intelligent optimization algorithms [13]. Normally, precise algorithms could achieve the global optimal with surprisingly high computational com-plexity, while intelligent optimization algorithm could only achieve the suboptimal solution with high accuracy and small time complexity. The performance of approximation algo-rithm is between both. Meanwhile, if the static environ-ment is considered, the common optimization solver can be used to solve the problem. However, in practical network environments, there are too many random attributes such as link congestion. As the network environment is constantly changing, we need to predictively obtain the backup strategy quickly. Thus, the traditional method is no longer applicable. Fortunately, Reinforcement learning (RL) algorithms can be exploited to make sequential decisions towards the long-term objective by continuously interacting with the environment.

**IV. Q-LEARNING BASED VNF BACKUP ALGORITHM**

We consider to back up some VNFs of an existing request in a network with limited resources. As the request arrives in sequential order, it is unnecessary to consider all requests simultaneously. Thus, we will back up each request one by

75900

one in this paper. In this case, the problem is transformed into a cost minimization problem about how to back up a parallel SFC with least bandwidth and computing resource occupation under some constraints in a dynamic network environment. RL is especially appropriate for solving deci-sion problems in dynamic environments. This inspires us to use Q-learning algorithm to solve the problem of (24), and obtain a backup scheme for parallel SFC that meets reliability requirement.

1. **Q-LEARNING BASED HIGH RELIABILITY BACKUP ALGORITHM**

The backup procedure can be modeled as a Markov Deci-sion Process (MDP), in which the transition probability is unknown. Thus, we intend to adopt Q-learning algorithm to solve our problem under the MDP framework. Q-Learning (QL) is a representative algorithm for reinforcement learning. It does not need to know the environment model and can be used for continuous tasks. The backup decision maker is mod-eled as an agent to choose the best backup candidate nodes for each service, thereby improving the reliability. When a node is selected or cancelled, the reliability of the service changes and the resource status in the network also changes. Therefore, the MDP can be represented as *M* D f*S*; *A*; *P*; *R*g, where *S* represents state, *A* represents action, *P* denotes the transition probability, which is unknown in our system, and *R* represents the reward. The details of the model are elaborated as follows.

*Agent:* The controller for making SFC deployment deci-sions, such as the Management and Orchestration (MANO) entity of NFV [14].

*State S:* We use the backup node selection status of eachrequest, reliability of each VNF, and the network status to represent the system state. Let *S* be the entire possible state space, and *s*(*t*) 2 *S* is the state at time *t*. Let there be *V* physical nodes and *E* links in the network. If the deployed parallel SFC includes *F* VNFs, we have *s*(*t*) D [(*j*; *k*); 1; 2; : : : ; *F* ; *c*1; *c*2; : : : ; *cN* ; *b*1; *b*2; : : : ; *bE* ], where (*j*; *k*); 1 6 *j* 6 *F*; 1 6 *k* 6 *N* means the backup status at time. If (*j*; *k*) D 1, it means the that the VNF *j* is backed up in the node *k*, otherwise, (*j*; *k*) D 0. *i* is the reliability of the working VNF. *ci*(*ci* > 0) means the available idle computing resource and *bi*(*bi* > 0) means the available bandwidth resource of link *i*.

*Action A:* We de ne the selection of VNF backup nodesas the action. When a VNF needs to be backed up, a certain node in the network is selected as the backup node according to certain constraints. Thus, we de ne the action as *a*(*t*) 2 *A*, *a*(*t*)D(*a*1; : : : ; *ai*; : : : *aN* ); *ai* 2 f0;1g, where *ai* D1 meansthat the physical node *i* is selected as the backup node at time *t*, otherwise, *ai* D 0 means that the physical node *i* is abandoned as the backup node at time *t*.

*Transition Probability P:* Let *P* D f*pas*;*s*0j*s*; *s*02 *S*; *a* 2 *A*grepresent the set of transition probabilities of the states.

D *P*[*s*(*t* C 1) D *s*j*s*(*t*) D *s*0; *a*(*t*) D *a*] means that

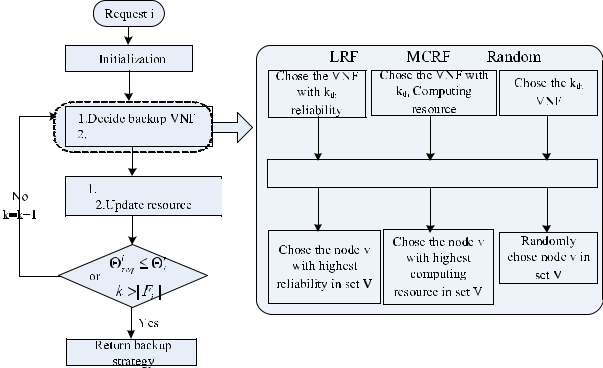
VOLUME 8, 2020

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| the transition probability of performing action *a* from current | | | | | | | | | | | | | | | | | | | | | | | | | | where *Q*(*s*; *a*) is the *Q* value in the state-action matrix under | | | | | | | | | | | |  |
| state *s* to next state *s*0. | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | action *a* and state *s*. | | | | |  |  |  |  |  |  |  |  |
| *Reward R:* When action *a*(*t*) is performed, the correspond- | | | | | | | | | | | | | | | | | | | | | | | | | | When a speci c action is performed, the system enters the | | | | | | | | | | | |  |
| ing reward will be obtained. Many factors should be taken | | | | | | | | | | | | | | | | | | | | | | | | | | next state, obtains a feedback value at the same time, and | | | | | | | | | | | |  |
| into consideration when de ning the reward function. First, | | | | | | | | | | | | | | | | | | | | | | | | | | updates *Q* value iteratively according to the following training | | | | | | | | | | | |  |
| the state *s*0(*t*) after taken action *a*(*t*) should satisfy all the | | | | | | | | | | | | | | | | | | | | | | | | | | function | | |  |  |  |  |  |  |  |  |  |  |
| constraints of (6) (14); (19); (22). Thus we de ne *R*(*s*; *a*) | | | | | | | | | | | | | | | | | | | | | | | | | | *Q*(*s*; *a*) | | D | *Q*(*s*; *a*) | C | [*r* | C | max *Q*(*s*0; *a*0) *Q*(*s*; *a*)]; | | | (31) | |  |
| as (25) if all constraints are satis ed and otherwise,*R*(*s*; *a*) D | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |  | *a*0 |  |  |  |  |  |
| , where is a penalty factor, | | | | | | | | | | | | | | | | | | | which | | | is a suf ciently | | | | where *s*0 and *a*0 represent the next state and next action respec- | | | | | | | | | | | |  |
| large positive real number. As our performance is jointly | | | | | | | | | | | | | | | | | | | | | | | | | |  |
| tively. > 0 is the learning rate, and is the discount factor. | | | | | | | | | | | |  |
| determined by reliability, delay, and resource occupation rate, | | | | | | | | | | | | | | | | | | | | | | | | | |  |
| It can be seen that the larger the learning rate , the less the | | | | | | | | | | | |  |
| we de ne the reward function as | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  | effect of retaining from the previous training. The larger the | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  | *R*(*s*; *a*)D *Rre*(*s*; *a*) *Rd* (*s*; *a*) *Rce*(*s*; *a*); | | | | | | | | | | | | | | | | | | | | | | (26) | discount factor , the greater the role of subsequent decisions. | | | | | | | | | | | |  |
|  |  |  | After that, the Agent performs a loop operation on the next | | | | | | | | | | | |  |
| where | | *Rre*(*s*; *a*) | | | | is the reliability reward | | | | | | | | | | | | | | | | function | | | at state | state until the optimal value *Q* (*s*; *a*) in the Q-value matrix | | | | | | | | | | | |  |
| *s*(*t*)D[(*j*; *k*);1;2; : : : ; *F* ; *c*1; *c*2; : : : ; *cN* ; *b*1; *b*2; : : : ; *bE* ]. | | | | | | | | | | | | | | | | | | | | | | | | | | *Q*(*s*; *a*) satis es the Bellman equation | | | | | | | | V |  |  |  |  |
| *Rre*(*s*; *a*) is de ned as | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | (32) | |  |
|  |  |  |  |  |  |  |  |  |  |  | 1; | | | | *if* | | | | > |  | *req* | |  |  |  |  |  |  | *Q* (*s*; *a*)D *E*[*r* Cmax *Q* (*s*0; *a*0)]: | | | | | | |  |
|  |  |  |  | *Rre*(*s*; *a*)D( | | | | | | | | | ; | | *otherwise* | | | | | | |  | ; |  | (27) | Compared with traditional statistic backup solutions, our pro- | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | posed Q-Learning based high reliability backup algorithm is | | | | | | | | | | | |  |
| where | |  | is the service reliability after backup. *Rd* (*s*; *a*) is the | | | | | | | | | | | | | | | | | | | | | | | more exible as it updates states through iterative interactions | | | | | | | | | | | |  |
| delay reward and is de ned as [15]: | | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |  | with the network. When for solving problems such as network | | | | | | | | | | | |  |
|  |  |  |  |  | 8 | 0; | |  |  |  |  |  |  |  |  |  |  |  | *t*N> | | | | | |  | congestion, busy computing resources, and node outages | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  | *t*N |  |  |  |  |  | occur in the network, the Q-learning algorithm can update the | | | | | | | | | | | |  |
| *R* |  | (*s*; *a*) | | D |  |  |  |  |  |  |  |  |  |  |  | ; |  |  | | > *t* | | | ; (28) | backup scheme in real time according to the current network | | | | | | | | | | | |  |
|  | 1 | | | |  | ( 1) | | | | | | |  |
|  | *d* |  |  | > |  |  |  |  |  | N > |  | status and make dynamic adjustments. The Q-Learning based | | | | | | | | | | | |  |
|  |  |  |  |  | > |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  | < |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  |  |  |  | > | 1; | |  |  |  |  |  |  |  |  |  |  |  | *t*N< | | | |  |  |  | high reliability backup algorithm is illustrated as algorithm 1. | | | | | | | | | | | |  |
|  |  |  |  | average> | | | SFC mapping delay, and is the delay | | | | | | | | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |
| where | |  | is the | | : |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| tolerant factor. If the delay of the backup link is increased too | | | | | | | | | | | | | | | | | | | | | | | | | | **Algorithm 1** : Q-Learning Based High Reliability Backup | | | | | | | | | | |  |  |
| much to satisfy the URLLC requirement, it will be an invalid | | | | | | | | | | | | | | | | | | | | | | | | | | Algorithm | | |  |  |  |  |  |  |  |  |  |  |
| backup. | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 1: | **Step 1: Initialization** | | | | | |  |  |  |  |  |  |
| *Rce*(*s*; *a*) is the resource occupation reward function and is | | | | | | | | | | | | | | | | | | | | | | | | | | 2: | Initialize *Q* D 0, state value *s* 2 *S*, action *a* 2 *A*, learning | | | | | | | | | | |  |
| de ned as | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | rate , and discount factor . | | | | | | |  |  |  |  |  |
|  |  |  | *Rce*(*s*; *a*)D | | | | | | | | | | | *ci* | |  | C | | ! | |  |  | *bi* | | (29) | 3: | Obtain current reward *r*(*s*; *a*). | | | | | | |  |  |  |  |  |
|  |  |  |  |  |  |  | **Step 2: Chose and execute action** | | | | | | | |  |  |  |  |
|  |  |  |  | | |  | | | ; | 4: |  |  |  |  |
|  |  |  | *Ctotal* | | | *Btotal* | | |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  | P |  |  |  |  |  |  | P | |  |  |  | 5: | Chose an action based on " *greedy* algorithm. | | | | | | | | |  |  |  |
| where *Ctotal* is the sum of all computing resources of the | | | | | | | | | | | | | | | | | | | | | | | | | | 6: | If the chosen action *a*0 2 *A*, obtain current reward *r*(*s*; *a*) | | | | | | | | | | |  |
| physical nodes, and *Btotal* | | | | | | | | | | | is the sum of bandwidth resources | | | | | | | | | | | | | | |  | and observe next state *s*0. | | | | | | |  |  |  |  |  |
| of the | | physical | | | | link. The | | | | | | |  | coef cients | | | | | | and ! represent | | | | | | 7: **Step 3: Update Q value** | | | | | | | |  |  |  |  |  |
| weight values, satisfying C ! D 1. At state *s*, considering | | | | | | | | | | | | | | | | | | | | | | | | | |  | *Q*(*s*; *a*)C[*r*(*s*; *a*)C | | |  |
| 8: | Update Q value based on *Q*(*s*; *a*) | | | | | | |  |  |
| the backup relationship (*j*; *k*), the VNF is unnecessary to | | | | | | | | | | | | | | | | | | | | | | | | | |  | max *Q*(*s*0; *a*0) | | | | *Q*(*s*; *a*)]. | | |  |  |  |  |  |
| backup if the backup node is the same as the original working | | | | | | | | | | | | | | | | | | | | | | | | | |  |  | *a*0 |  |  |  |  |  |  |  |  |  |  |
| node. Meanwhile, to occupy as few resources as possible, | | | | | | | | | | | | | | | | | | | | | | | | | | 9: **Step 4: Update state** | | | | | | |  |  |  |  |  |  |
| 10: Update state as *s* D *s*0, repeat Step 2. | | | | | | | | | |  |  |  |
| the value of the reward function should be greater if the | | | | | | | | | | | | | | | | | | | | | | | | | |  |  |  |
| occupied resource is less. | | | | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| **B. THE Q-LEARNING BASED HIGH RELIABILITY** | | | | | | | | | | | | | | | | | | | | | | | | |  | **V. SIMULATION AND RESULT ANALYSIS** | | | | | | | | | |  |  |  |
| **BACKUP ALGORITHM** | | | | | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | Based on the analyzing result of [5] [7], [9] that the service | | | | | | | | | | | |  |
| The Q-learning algorithm is a value-iterative algorithm, | | | | | | | | | | | | | | | | | | | | | | | | | | reliability can be improved by backing up related virtual net- | | | | | | | | | | | |  |
| which has nothing to do with the environment model, and | | | | | | | | | | | | | | | | | | | | | | | | | | work functions (VNFs), in this paper we develop a Q-learning | | | | | | | | | | | |  |
| thus it does not depend on the state transition matrix. The | | | | | | | | | | | | | | | | | | | | | | | | | | based algorithm (QL-P) for parallel SFC to obtain the opti- | | | | | | | | | | | |  |
| state-action matrix *Q* is the key to the Q-learning algorithm. | | | | | | | | | | | | | | | | | | | | | | | | | | mized VNF backup strategy ef ciently. And then, we verify | | | | | | | | | | | |  |
| At any time *t*, the corresponding action *a* is chosen based on | | | | | | | | | | | | | | | | | | | | | | | | | | the advantage of our proposed QL-P algorithm by comparing | | | | | | | | | | | |  |
| the state-action matrix *Q*, and it should satisfy | | | | | | | | | | | | | | | | | | | | | | | | |  | the performance of different VNF backup strategies obtained | | | | | | | | | | | |  |
|  |  |  |  |  |  |  | *Q*(*s*; *a*) | | | D | | | max | | | *Q*(*s*; *a*) | | | | ; |  |  |  |  | (30) | by different algorithms. To the best of our knowledge, there | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  | is no existing known algorithm for the parallel SFC backup | | | | | | | | | | | |  |
|  |  |  |  |  |  |  |  |  |  |  | *a* | f |  |  |  | g |  |  |  |  |  |  |  |
| VOLUME 8, 2020 | | | |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | 75901 | |  |

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

**FIGURE 5.** Flowchart of LRF, MCRF and Random algorithms.



problem can be used as comparison reference. Thus, we use three heuristic based backup strategies for performance eval-uation of our proposed algorithm, namely Lowest Reliability First (LRF), Minimum Computing Resource First (MCRF), and Random algorithms. To highlight the advantage of the parallel SFC, the Q-learning based algorithm is realized for both parallel SFC and sequential SFC back up. Thus, ve algorithms are compared to verify the performance of our proposed algorithm in this section, which are parallel SFC based Q-learning (QL-P) algorithm, reliability- rst algo-rithm, computing-resource- rst algorithm, random backup, and sequential SFC-based Q-learning (QL-S).

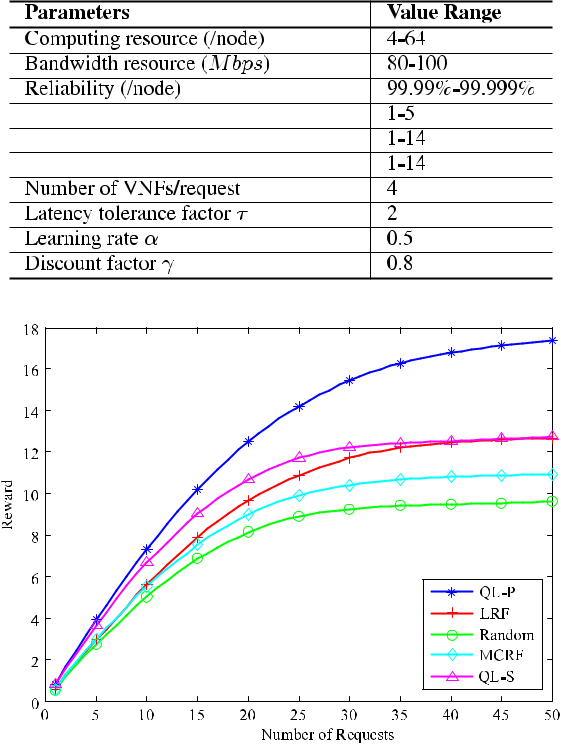
As shown in Fig. 5, the LRF algorithm starts from exam-ining the reliability of the SFC. When the reliability of the SFC does not meet the conditions, the most reliable node of the physical node is backed up to the less reliable VNF in the SFC under the constraint conditions. The MCRF algorithm considers the limited computing resources. When the request does not meet the reliability requirements, the node with the most abundant computing resources is selected as the backup node. The Random algorithm only considers reliability. When the reliability of the request does not meet the conditions, the backup node is randomly selected under the constraint of the backup node. To evaluate the performance of the proposed QL-P algorithm, we assume that one VNF is required to be backed up to meet the service reliability requirement. However, the QL-P algorithm is also feasible for the situation that more than one VNFs backup is required.

1. **SIMULATION ENVIRONMENT AND PARAMETERS SETTING**

The network topology considered in this paper has 14 nodes, 21 links, and the computing resources are counted with the number of processor cores of the physical nodes. The computing resources of each node are any number between 4 to 64. The bandwidth of each link is any between 80*Mbps* to 100*Mbps* [16], [17], and the reliability of each node is between 0.9999 to 0.99999 [17]. Commonly, the number of VNFs for each service request is 4, and the deployment of backup VNF requires The computing resources are uniformly

75902

**TABLE 1.** Simulation parameters.



**FIGURE 6.** Reward comparison with increasing backed up request.

distributed in [1, 5]. The latency tolerance factor due to backups is 2. The learning rate D 0:5, and the discount factor D 0:8. All parameters are illustrated as table 1. The following performance metrics are used to evaluate the performance of our proposed backup scheme.

1. *Delay*: The average network function execution delay

*Ted* .

1. *Reliability*: The reliability of the entire service afterbackup *i*0.
2. *Computing occupation ratio*: All computing resourcesrequested for backup reservation *Ratioc*, *Ratioc* D

P P P

*xik*;*j* *ci*;*j*.

1. *bandwidth occupation ratio*: All bandwidth resourcesrequested for backup reservation *Ratiob*, *Ratiob* D

P P P

*ym* *b* .

*i*;*j* *i*

* 1. **NUMERICAL RESULTS AND DISCUSSIONS**

1. REWARD

Fig. 6 shows the cumulative reward function as a function of the number of requests. We can observe that as the number of requests continues to increase, the value of the reward function continues increasing and eventually converges to a xed value. In the same situation, the Q function is the highest reward function, while the stochastic algorithm has the lowest reward function. The de nition of the reward function in the Q-learning algorithm is related to the three aspects of

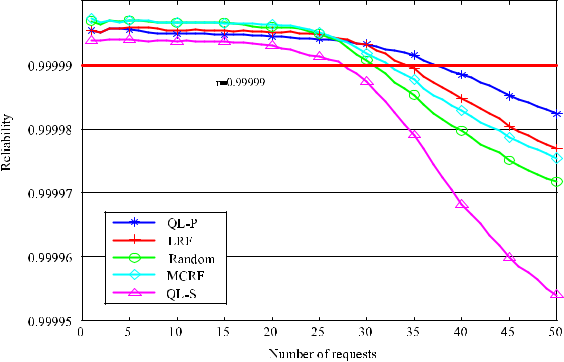
VOLUME 8, 2020

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

reliability, resource occupancy, and average execution net-work function delay. The LRF algorithm backup method considers physical nodes with high reliability nodes to ensure high reliability. The value of the reward function of LRF is higher than that of Random and MCRF. The MCRF algorithm considers selecting a physical node with more resources as a backup node to ensure less resource occupation. When the Random algorithm is used, the backup node is randomly selected without considering reliability, resource occupation, and delay, so the reward value obtained is relatively low. Meanwhile, when the sequential SFC adopts the Q-learning algorithm under the same circumstances, the return obtained is lower than the return value of the parallel SFC. It is because the introduction of network function parallelism makes fewer physical nodes mapped.

2) RELIABILITY

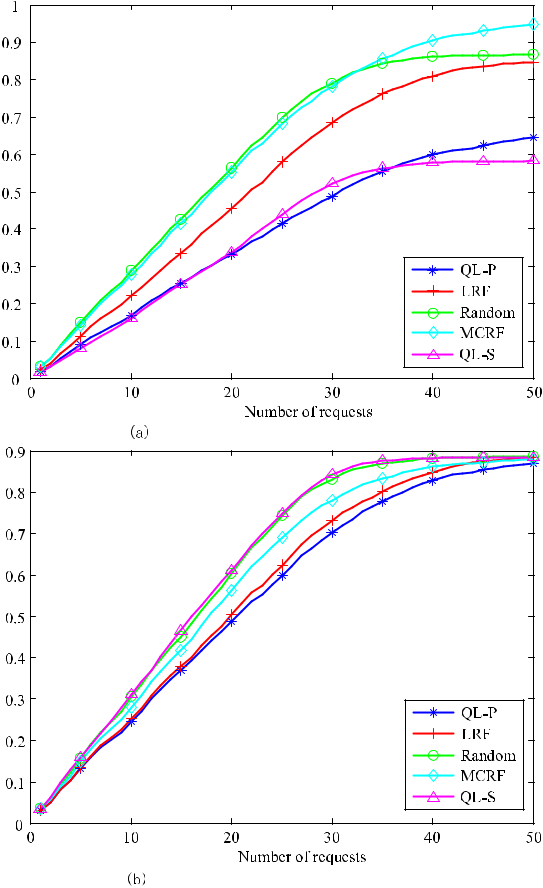
The reliability comparison among all the algorithms is illus-trated as Fig. 7. We can see that the reliability decreases with the number of backed up requests. The is due to the limited physical resources in the underlying network, as the number of backed up service requests increases, the sys-tem cannot provide suf cient resources to meet the backup requirement for all service requests. When system resources are suf cient, all algorithms can meet the reliability require-ments of the service. According to the de nition of the reward function, the reward value equals 1 if the reliability constraint is satis ed. In this case, as the Q-learning based algorithm comprehensively considers the trade-offs between reliability, resource occupation and delay, it is less reliable than other algorithms. However, in the resource limited sce-nario, Q-learning considers the balance between resource occupation and reliability, so it can satisfy more requests. Meanwhile, if the reliability does not meet the reliability requirements, the Q-learning based algorithm can obtain the maximum reliability compared to the other algorithms. The QL-S algorithm is dedicated for sequential SFC, so differ-ent VNFs have to be deployed on different physical nodes. However, as parallel network functions in the parallel SFC can be deployed and executed on the same physical node,



the number of involved physical nodes for an SFC in the parallel execution way is less than that for the same SFC in the sequential execution way. Based on the calculation of reliability, it can be known that the more physical nodes mapped by the VNF, the lower the reliability, so that the more resources need to be backed up to achieve the same reliability. Obviously, the Q-learning algorithm is appropriate to meet the reliability requirements of URLLC scenarios in 5G, and it can obtain higher reliability when resources are insuf cient.

3) RESOURCE OCCUPANCY

Fig. 8 shows a comparison of bandwidth and comput-ing resource occupancy. As the number of SFC requests increases, the resources occupied by VNF backups grad-ually increase accordingly. When the underlying physical resources cannot provide backups service, the resource occu-pation tends to stabilizing. The Q-learning based algorithm considers resource occupation as a part of the reward func-tion, and thus the Q-learning method uses the least computing and bandwidth resources. Fig. 8 (a) shows the comparison of bandwidth resource occupancy rate for different algo-rithms. Using the Q-learning based algorithm can reduce the bandwidth occupancy rate for both parallel SFC and sequential SFC backup, and the difference of bandwidth

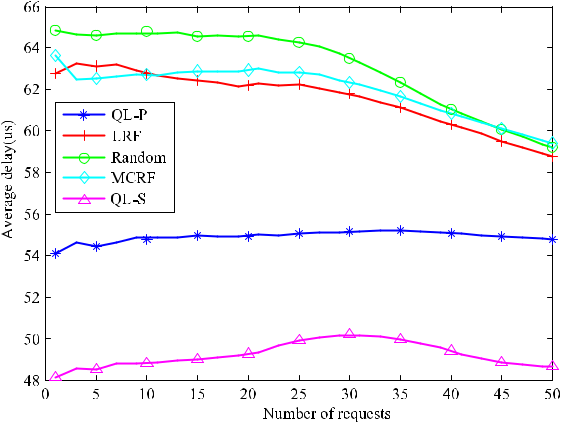


**FIGURE 7.** Reliability comparison with increasing backed up request. **FIGURE 8.** Resource occupancy comparison.

VOLUME 8, 2020 75903

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

**FIGURE 9.** The average network function execution delay comparison.



resources occupation is very little for the sequential SFCs and parallel SFCs. The MCRF algorithm, LRF algorithm, and Random algorithm select backup nodes with the most computing resources, maximum reliability, and randomness at the time of backup. They do not consider the limitations of bandwidth resources. Therefore, these three algorithms occupy more bandwidth than the Q-learning based algorithm. The comparison of computing resource occupation rate is shown as Fig. 8(b). We can observe that compared with other algorithms, the Q-Learning based algorithm occupies less computing resources, but the QL-S algorithm occupies more computing resources. This is because that the sequential SFCs require more VNFs to be backed up for the same reliability, which may result in more computing resources occupied.

It is obvious that the Q-Learning based algorithm can occupy the least bandwidth and computing resources, obtain the greatest reliability improvement, and effectively uti-lize the remaining resources in the actual physical network topology.

1. THE AVERAGE EXECUTION TIME OF NETWORK FUNCTION

The average execution time of network function for different algorithms is compared in Fig. 9. We can observe that in the same environment, the QL-P algorithm can reduce the average execution time by 20% compared with the LRF, MCRF, and Random algorithms. The average execution time of the QL-S algorithm is 12.5% lower than that of the QL-P algorithm. The average execution time of the QL-P algorithm and the QL-S algorithm is relatively stable. The average execution time is a part of the value of the reward func-tion. When selecting a backup node, the node with the least delay will be considered as the deployment node. As the parallel network function needs to consider the parallel link during the backup, so the average execution is larger than the sequential network function. For LRF, MCRF and Random algorithms, when the number of the SFC requests is small, which means that resources are suf cient to provide backup service, the average execution time is stable. As the number of SFC requests to be backed up increases, the average execution

75904

time decreases due to the resources are insuf cient to provide backup service. It is because that based on the de nition of average delay, when no backup is selected for a VNF, the average delay is equal to the average delay of the working VNF. Thus, the backups cannot be completed when there are insuf cient resources and the average delay is reduced. Obviously, the QL-P algorithm can obtain a smaller average delay, and when a network function is migrated to a backup physical node for execution, the end-to-end delay difference is smaller.

**VI. CONCLUSION**

In this paper, we have addressed the requirements of low-latency and high-reliability scenarios for 5G networks. We have considered the issue of improving reliable backup of parallel SFC, and proposed a Q-learning-based backup mechanism to obtain the optimal backup solutions in resource-constrained networks. To satisfy the high reliability requirement, the backup deployment of parallel SFC is rstly considered by jointly considering the impact of reliability improvement, resource consumption, as well as the impact of additional delays, brought by selecting a VNF backup node. Simulation experiments show that the algorithm can meet the reliability requirements of low-latency and high-reliability scenarios with the lowest resource consumption, and con-siders the problem of increased delay caused by backup. Compared with traditional algorithms, Q-learning algorithm has great advantages and is suitable for the backup problem of parallel SFC.

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VOLUME 8, 2020

J. Zhou *et al.*: Network Function Parallelization for High Reliability and Low Latency Services

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GANG FENG (Senior Member, IEEE) received the B.Eng. and M.Eng. degrees in electronic engi-neering from the University of Electronic Science and Technology of China (UESTC), in 1986 and 1989, respectively, and the Ph.D. degree in infor-mation engineering from The Chinese University of Hong Kong, in1998. He joined the School of Electric and Electronic Engineering, Nanyang Technological University, in December 2000, as an Assistant Professor and promoted as an Associate



Professor, in October 2005. He is currently a Professor with the National Laboratory of Communications, UESTC. He has extensive research experi-ence and published widely in computer networking and wireless networking research. His research interests include resource management in wireless networks, next generation cellular networks, and so on.

JIANHONG ZHOU (Member, IEEE) received the M.Eng. degree in electronics and electrical engi-neering from Nanyang Technological University (NTU), Singapore, in 2008, and the Ph.D. degree in computer software and theory from the Uni-versity of Chinese Academy of Sciences, in 2016. She is currently an Associate Professor with the School of Computer and Software Engineering, Xihua University, China. She also holds a postdoc-toral position with the National Key Laboratory



of Science and Technology on Communications, University of Electronic Science and Technology of China (UESTC). Her research interests include next generation cellular networks, the IoT, low-latency ultra-reliable com-munication, arti cial intelligence, and so on.

YI GAO (Member, IEEE) received the B.Eng. and M.Eng. degrees in communication and infor-mation system from the University of Electronic Science and Technology of China (UESTC), in 2016 and 2019, respectively. His research interests include next generation cellular net-works, network function virtualization, ultra reli-able and low-latency communication, and the industrial IoT.



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| VOLUME 8, 2020 | 75905 |