Multi-domain Cooperative Service Fault Diagnosis Algorithm Under Network Slicing with Software Defined Networks

Wei Li[1], Yong Dai[1], Yong Xu[1], Xilao Wu[1], Wei Li[1], and Peng Lin[2](✉)

[1] Communication Branch, State Grid Jiangsu Electric Power Co., Ltd., Jiangsu, China
[2] Beijing Vectinfo Technologies Co., Ltd., Beijing, China
linpeng@vectinfo.com

Abstract. In order to solve the problem of low accuracy of fault diagnosis algorithms in multiple management domain environments such as such as Software Defined Networks (SDN), this paper proposes a multi-domain cooperative service fault diagnosis algorithm under network slice based on the correlation between faults and symptoms. According to the relationship between the management domain and the symptoms, the network resources corresponding to the symptoms are divided into resources within the management domain and inter-domain resources. When constructing a suspected fault set, the suspected fault set is constructed according to the number of simultaneous faults, and the final suspected fault set is determined by calculating the interpretation capability of the suspected fault. Finally, according to Bayesian theory, the fault set with the highest probability is regarded as the most probable fault set. Compared with the existing classical algorithms in the experimental part, it is verified that the algorithm in this paper improves the accuracy of fault diagnosis and reduces the false alarm rate of fault diagnosis.

Keywords: SDN network · Network slicing · Fault diagnosis · Management domain

1 Introduction

With the rapid construction and operation of next generation networks, the application scope of various network-based services in production and life is gradually increasing. In order to improve the reliability of the network, network virtualization technology such as Software Defined Networks (SDN) has been applied to 5G networks [1]. In this context, existing networks are divided into underlying networks and virtual networks. The underlying network is responsible for the construction of the underlying network nodes and the underlying network links. The virtual network leases network resources from the underlying network to run specific 5G services. When network resources fail, how to quickly and accurately locate the fault has become a key issue that network operators urgently need to solve.

M. Cheng et al. (Eds.): SmartGIFT 2020, LNICST 373, pp. 55–64, 2021.
https://doi.org/10.1007/978-3-030-73562-3_5

The network fault diagnosis algorithm mainly adopts two strategies: passive detection [2] and active detection [3]. The main advantage of passive detection is simple implementation, and the main disadvantage is the low accuracy of the fault diagnosis model constructed. Active detection can better improve the performance of the fault diagnosis algorithm by selecting the detection strategy in advance, but the design of detection is more complicated. For example, literature [4] uses a dependency matrix to construct a detection model, which better solves the problem of single-point fault diagnosis. In terms of multi-layer fault diagnosis, the general method is to resolve the multi-layer model into a two-layer model based on the network resource relationship [5]. For the problems of complex network topology and low performance of fault diagnosis algorithms brought about by the large-scale network, literature [6] uses artificial intelligence algorithms to construct learning models, which better solve the problem of low performance of fault diagnosis algorithms in large-scale environments.

The existing research mainly solves the fault location in a single domain. However, when the network scale becomes larger and larger, multiple network operators will jointly build and manage the network, thereby forming multiple management domains. Each domain is responsible for network resource allocation and fault management in the area. When a virtual network service fails, each domain only knows its own internal failure information. When faults cannot be located within a domain, the problem of how multiple domains can collaborate to locate faults has not been well resolved. To solve this problem, this paper proposes a multi-domain cooperative service fault diagnosis algorithm under network slicing with SDN. The algorithm improves the performance of the fault diagnosis algorithm through the cooperation of multiple management domains.

2 Problem Description

Network slicing is an on-demand networking method that allows operators to separate multiple virtual end-to-end networks on a unified infrastructure. Each network slicing is carried out from the wireless access network, the bearer network to the core network. In a network slice, it can be divided into at least three parts: wireless network sub-slice, bearer network sub-slice and core network sub-slice. The core of network slicing technology is network function virtualization. Network function virtualization separates the hardware and software parts from traditional networks. The hardware is deployed by a unified server, and the software is undertaken by different network functions, thereby realizing the needs of flexible assembly services. Network slicing is based on a logical concept and is the reorganization of resources. Reorganization is to select the required virtual machines and physical resources for a specific communication service type according to the service level agreement.

In the network slicing environment, in order to distinguish the existing network from the sliced network resources, the physical network resource is called the underlying network, and each sliced resource is called the virtual network. Use undirected weighted graph $G^S = \left(N^S, E^S\right)$ to represent the underlying network. Use undirected weighted graph $G^V = (N^V, E^V)$ to represent the virtual network. $n_i^s \in N^S$ and $n_i^V \in N^V$ represent the underlying node and virtual node, respectively, and $e_j^s \in E^S$ and $e_j^V \in E^V$ represent the underlying link and the virtual link, respectively. Because the virtual network allocates resources by the underlying network, use $Mapping_N : \left(N^V \to N^S, E^V \to P^S\right)$

to represent the resource allocation relationship between the virtual network and the underlying network. Among them, $N^V \rightarrow N^S$ indicates that the underlying node n_i^s allocates resources to the virtual node n_i^V, and $E^V \rightarrow P^S$ indicates that the underlying path P^S allocates resources to the virtual link e_j^V. The bottom-level path P^S refers to the bottom-level link resource composed of multiple end-to-end connected bottom-level links e_j^s. The start and end points of the path respectively correspond to the bottom-level nodes mapped by the two virtual nodes of the virtual link.

When the virtual network covers a large area, multiple domains need to cooperate with each other to meet the resource requirements of the virtual network. The service model of multi-domain collaboration is shown in Fig. 1. It contains 3 management domains. The virtual network uses the network resources of these three management domains to construct a virtual network. When a virtual resource on a virtual network fails, the cooperation of the three management domains is required to quickly locate the root cause of the failure.

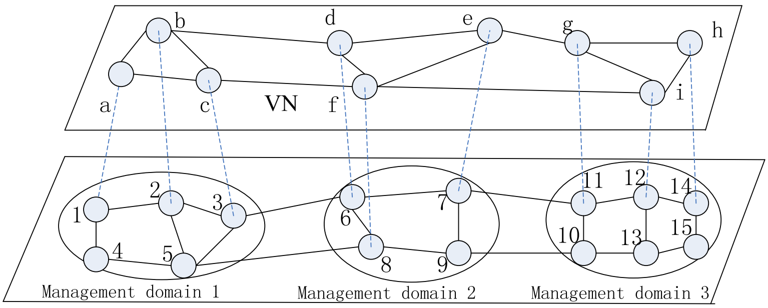

Fig. 1. Multi-domain collaboration service model

3 Fault Propagation Model

Because all users want a reliable network, fault management is one of the most basic functions of network management. When a component in the network fails, the network manager must quickly find the root cause of the fault and troubleshoot it in time. Under normal circumstances, it is unlikely that a fault can be quickly isolated, because the factors that cause network faults are usually very complex, especially those caused by multiple network components. In this situation, we should generally repair the network first, and then analyze the cause of the failure. The recurrence of similar failures can be prevented by analyzing the causes of failures, which is very important for the reliable performance of the network. The goal of fault management is to resume normal service operations as soon as possible, minimize the negative impact of component failure on the business, and ensure that the service level goals and service level quality agreed with the business customers in advance are met.

In order to quickly locate faults, a fault propagation model is constructed based on Bayesian theory, so as to correlate the observed symptoms with the actual network environment. The Bayesian network is a directed acyclic graph G(V, E). The node V in the graph represents a variable, and the directed edge E connecting the nodes represents a dependency between the nodes. Each node stores a conditional probability table, which indicates the influence of the value of its parent node on the state of the node. If the node is the root node, the conditional probability of the node records the prior probability of this node. The fault propagation model is shown in Fig. 2, including symptom, fault, and directed line from fault to symptom.

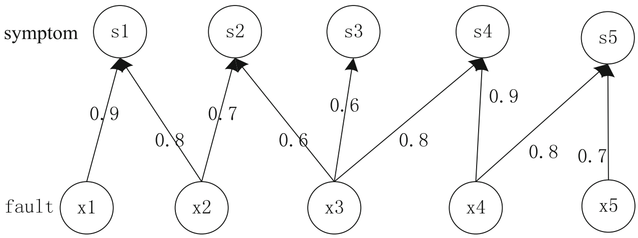

Fig. 2. Fault propagation model based on Bayesian theory

Symptoms refer to the working status of various businesses running on the virtual network. Symptom set $S_o = \{s_1, s_2, ..., s_m\}$ represents a set of m symptoms. When the business is running normally, it is called a positive symptom and is represented by $s_m = 0$. When the business fails to operate normally, it is called a negative symptom and is represented by $s_m = 1$. Failure refers to the working status of the underlying network resources. The set of suspected faults $X = \{x_1, x_2, \ldots, x_n\}$ represents a set of n suspected faults x. When the underlying network resources are operating normally, use $x_n = 0$ to indicate. When the underlying network resources are abnormal, use $x_n = 1$ to indicate. The directed line from failure to symptom indicates the probability that when the underlying network resource is abnormal, the symptom status of the service carried on the underlying network resource is negative.

4 Algorithm

This paper proposes a multi-domain cooperative service fault diagnosis algorithm under network slice (MCSFDA) with SDN as shown in Fig. 1. The algorithm includes the following three processes. (1) Symptom collection and fault decomposition, (2) Building Bayesian model, (3) Fault set location. In step (1), each virtual network service provider reports symptoms and fault information to the fault management center, and the fault center performs fault decomposition based on the collected symptoms and network topology, and sends the fault information to the corresponding management domain. In step (2), each management domain uses detection technology to obtain the network performance of each faulty node, and feeds the results back to the fault management center. For links between domains, related domains need to send data packets to each other to obtain the packet loss rate of the link. For example: in Fig. 1, the path (1–2–3) belongs to domain 1, the link (6–7) belongs to domain 2, the path (11–12–14) belongs to domain 3, and the link (3–6) belongs to the shared resources of domain 1 and domain 2, links (7–11) belong to the shared resources of domain 2 and domain 3. The fault management center builds a Bayesian model based on the network performance fed back from each management domain. In the fault propagation model based on Bayesian theory, the symptom refers to the status of the virtual network service, and the fault refers to the detection result of the underlying link corresponding to the virtual network service. In step (3), to select the most suitable fault set from the set of suspected faults to realize fault location. It adopts two processes: constructing a set of suspected faults and locating faults based on Bayesian formula. Steps (1) and (3) are described in detail below.

4.1 Symptom Collection and Fault Decomposition

The end-to-end service $P^V\left(n_{p_1}^V, n_{p_m}^V\right)$ contains multiple virtual paths. From the process of mapping $E^V \to P^S$ from the virtual link to the underlying path, it can be seen that the end-to-end service $P^V\left(n_{p_1}^V, n_{p_m}^V\right)$ contains more underlying links. To facilitate the description of the underlying links included in the end-to-end service, it is necessary to map the end-to-end service to the underlying link. Use $e^V\left(n_k^V, n_l^V\right)$ to represent the virtual link between virtual nodes n_k^V and n_l^V, and use $P^V\left(n_{p_1}^V, n_{p_m}^V\right)$ to represent the virtual path between virtual nodes $n_{p_1}^V$ and $n_{p_m}^V$. $P^V\left(n_{p_1}^V, n_{p_m}^V\right)$ uses link to represent $e^V\left(n_{p_1}^V, n_{p_2}^V\right)$, $e^V\left(n_{p_2}^V, n_{p_3}^V\right), \ldots, e^V\left(n_{p_{m-1}}^V, n_{p_m}^V\right)$. Use $e^S\left(n_k^S, n_l^S\right)$ to represent the underlying link between the underlying nodes n_k^S and n_l^S, and use $P^S\left(n_{p_1}^S, n_{p_m}^S\right)$ to represent the underlying path between the underlying nodes $n_{p_1}^S$ and $n_{p_m}^S$. $P^S\left(n_{p_1}^S, n_{p_m}^S\right)$ use link to represent $e^S\left(n_{p_1}^S, n_{p_2}^S\right), e^S\left(n_{p_2}^S, n_{p_3}^S\right), \ldots, e^S\left(n_{p_{m-1}}^S, n_{p_m}^S\right)$.

According to the relationship of $E^V \to P^s$, convert $P^V\left(n_{p_1}^V, n_{p_m}^V\right)$ to $P^S\left(n_{p_1}^S, n_{p_m}^S\right)$. If the fault in $P^S\left(n_{p_1}^S, n_{p_m}^S\right)$ can be inferred based on the symptoms, the faulty resources can be repaired to ensure the quality of service. However, when the underlying link contained in $P^S\left(n_{p_1}^S, n_{p_m}^S\right)$ is provided by multiple underlying network resource management domains, multiple management domains need to cooperate with each other to complete fault diagnosis. Taking into account that each management domain can detect the failure of its own internal network resources, this paper divides $P^S\left(n_{p_1}^S, n_{p_m}^S\right)$ into the resources of path $P^S\left(I_{i,j}^{i+1}, E_{i,j}^{i+2}\right)$ in the management domain and inter-domain link $e\left(E_{i,j}^i, I_{i,j}^{i+1}\right)$ according to the characteristics of the management domain. Among them, $I_{i,j}^k$ represents the ingress gateway of the k-th SN_k, and $E_{i,j}^k$ represents the egress gateway of the k-th SN_k. For $I_{i,j}^k$, the constraints of $n_{p_1}^S \in SN_i, n_{p_m}^S \in SN_j, n_{p_n}^S \in SN_k$ and $n_{b_{n-1}}^S \notin SN_k$ should be satisfied. For $E_{i,j}^k$, the constraints of $n_{p_1}^S \in SN_i, n_{p_m}^S \in SN_j, n_{p_n}^S \in SN_k$ and $n_{p_{n+1}}^S \notin SN_k$ should be satisfied. Therefore, $P^S\left(n_{p_1}^S, n_{p_m}^S\right)$ can be expressed as

$e^S\left(n_{p_1}^S, E_{i,j}^i\right), e\left(E_{i,j}^i, I_{i,j}^{i+1}\right), P^S\left(I_{i,j}^{i+1}, E_{i,j}^{i+2}\right), \ldots, e\left(E_{i,j}^{j-1}, I_{i,j}^j\right)$. For example, the underlying network of the end-to-end service (a-b-d-e-g-h) in Fig. 1 can be divided into: the path in domain 1 (1–2–3), the inter-domain link (3–6), the path in domain 2 (6–7), the inter-domain link (7–11), and the path in domain 3 (11–12–14).

4.2 Fault Location

Fault set location includes two processes: constructing a set of suspected faults and locating faults based on Bayesian formula. When constructing a set of suspected failures, construct a set of suspected failures based on the number of simultaneous failures. The number of simultaneous failures is related to the number of network nodes and the probability of network node failures. Assuming that the probability of failure of the underlying network is 0.001 and network is composed of three network nodes, the probability of failure of two nodes at the same time is 3×10^{-6}. When constructing a set of suspected failures, a failure node is arbitrarily selected from the failure node set X, and placed into the candidate failure set m_{ik} (i represents the size of the candidate failure set, and k represents the sequence number of the set). The failure set $M_i (i = 1, \ldots, \max(\Omega, |X|))$ is gradually constructed until the end condition is met, that is, Ω nodes are included in m_{ik}. Among them, Ω represents the number of simultaneous failures.

In order to evaluate the value of m_{ik}, define $Abli_{ik}$ as the explanatory ability of m_{ik}. The calculation method is shown in formula (1). $Num_{A(s)=1}$ indicates the number of abnormal symptoms related to the suspected failure; $A(s) = 1$ indicates that the symptom s is abnormal, and the calculation formula is shown in formula (2). $Num_{A(s)=0}$ indicates the number of normal symptoms related to the suspected failure; $A(s) = 0$ indicates that the symptom s is abnormal, and the calculation formula is shown in formula (3). $pa(s)$ represents the parent node of symptom s.

$$Abli_{m_{ik}} = Num_{A(s)=1} + Num_{A(s)=0} \tag{1}$$

$$Num_{A(s)=1} = |\{s | s \in S_o, A(s) = 1, \exists x \in m_{ik}, x \in pa(s)\}| \tag{2}$$

$$Num_{A(s)=0} = |\{s | s \in S_o, A(s) = 0, \exists x \in m_{ik}, x \in pa(s)\}| \tag{3}$$

According to Bayesian theory, if the state of some nodes is known, formula (4) can be used to solve the maximum possible state of unknown node $X = \{X_1, X_2, ..., X_n\}$. Among them, $pa(T_j)$ represents the parent node of detecting T_j. N represents the number of nodes, and M represents the number of probes.

$$\begin{aligned} X^* &= \max_X P(X|T) = \max_X \frac{P(X,T)}{P(T)} = \max_X P(X,T) \\ &= \max_X \prod_{i=1}^{N} P(X_i) \prod_{j=1}^{M} P(T_j | pa(T_j)) \end{aligned} \tag{4}$$

Therefore, this paper uses formula (5) to calculate the probability of each $M_i (i = 1, .., \max(\delta, |Fs|))$, and regards the failure set with the largest probability as the most likely failure set. The nodes included in the failure set are the failed nodes.

$$P(M_i) = \prod_{X_i \in X} P(X_i) \prod_{T_j \in T} P(T_j | pa(T_j)) \tag{5}$$

5 Performance Analysis

5.1 Network Environment

In order to simulate the network topology in the network slicing environment, this article uses the GT-ITM [7] tool to generate the underlying network and virtual network topology to simulate the network slicing environment. In order to judge the performance of the algorithm in different network environments, the node size of the underlying network was increased from 100 to 500. The number of virtual nodes in the virtual network is uniformly distributed from 5 to 25, which is used to simulate virtual networks of different sizes. The mapping algorithm from the underlying network to the virtual network uses the classic mapping algorithm [8]. In order to simulate different management domains, the bottom network will be divided into 5 management domains according to the number of bottom network nodes. In terms of service simulation, this article takes end-to-end service as the research object. Select 10% of the virtual nodes from the virtual network as the source node. For each virtual source node, 3 nodes are randomly selected as destination nodes, and the shortest path algorithm is used to generate end-to-end services. In terms of fault injection, set the prior failure probability of the underlying network node to obey the uniform distribution of [0.001,0.01], and the conditional probability obey the uniform distribution of (0,1).

In order to analyze the performance of the algorithm MCSFDA in this paper, it is compared with the non-cooperative service fault diagnosis algorithm (NCSFDA). Different from the algorithm in this paper, each management domain of the algorithm NCSFDA sends the network performance to the management center, and the management center directly diagnoses the fault based on the mapping relationship between the virtual network and the underlying network. The evaluation indicators include the accuracy rate of fault diagnosis, false alarm rate, and diagnosis time. The accuracy rate refers to the proportion of the diagnosed faulty node set in the real faulty node set. The higher the accuracy rate, it means that the algorithm has identified more real faults and the algorithm performance is better. The false alarm rate refers to the proportion of false faults identified by the diagnostic algorithm in all identified faults. The higher the false alarm rate, it indicates that the algorithm mistakenly recognizes the normal network node as the fault node, and the performance is poor. Diagnosis time refers to the time taken by the algorithm from inputting network topology and service symptom information to outputting diagnosis results. The longer the diagnosis algorithm takes, the greater the time overhead of the algorithm.

5.2 Performance Comparison

The accuracy of fault diagnosis is shown in Fig. 3. The X-axis indicates that the number of network nodes has increased from 100 to 500, which is used to analyze the impact of different network sizes on algorithm performance. The Y axis represents the accuracy of the algorithm. It can be seen from the figure that the size of the network has a small effect on the accuracy of the fault diagnosis of the two algorithms, indicating that the diagnosis performance of the two algorithms has little relationship with the network topology. From the comparison of the accuracy of the two algorithms, the accuracy of this algorithm is high. This is because the algorithm in this paper can effectively improve the accuracy of the data in the fault diagnosis model through the collaboration of multiple domain managers, thereby improving the accuracy of fault diagnosis.

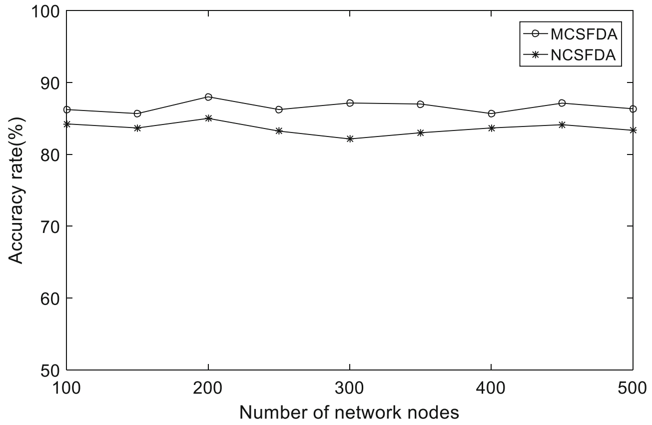

Fig. 3. Comparison of accuracy rate

The comparison result of the false alarm rate of fault diagnosis is shown in Fig. 4. The X axis represents the number of network nodes, and the Y axis represents the false alarm rate of the algorithm. It can be seen from the figure that the false alarm rate performance of the two algorithms has little to do with the network scale. The false alarm rate of the algorithm in this paper is lower than that of the traditional algorithm. The same is because the fault diagnosis model data of the algorithm in this paper is more accurate, which reduces the false alarm rate.

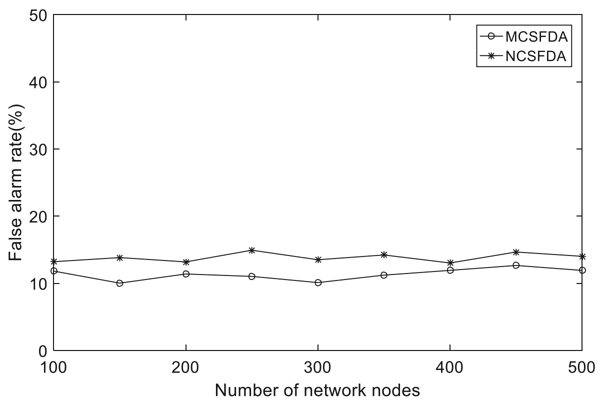

Fig. 4. Comparison of false alarm rate

The comparison of the duration of fault diagnosis is shown in Fig. 5. The X axis represents the number of network nodes, and the Y axis represents the fault diagnosis time of the algorithm. It can be seen from the figure that as the network scale increases, the diagnosis time of the two algorithms is increasing. This is because as the network scale increases, the fault propagation model increases, and the set of suspected faults also increases, which requires more time for fault diagnosis. In addition, the diagnosis time of the algorithm in this paper has increased rapidly. This is because, compared with traditional algorithms, it requires cooperation between various domains for active positioning, which requires a longer time overhead.

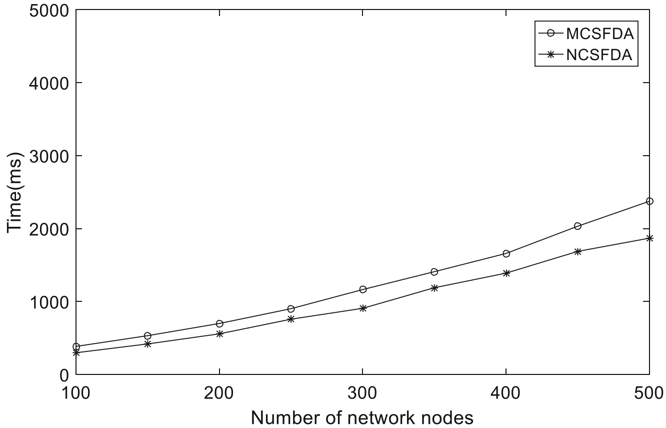

Fig. 5. Comparison of time

6 Conclusion

Accurate and rapid location of SDN network resource failures has become a key issue that network operators urgently need to solve. However, when network resources are composed of multiple management domains, the accuracy of service fault diagnosis across multiple domains is low. To solve this problem, this paper proposes a multi-domain cooperative service fault diagnosis algorithm under 5G network slicing with SDN. The algorithm includes three processes: symptom collection and fault decomposition, Bayesian model construction, and fault set location. In the symptom collection and fault decomposition steps, the fault center performs fault decomposition based on the collected symptoms and network topology, and sends the fault information to the corresponding management domain. In the step of constructing the Bayesian model, inter-domain links need related domains to send data packets to each other to obtain the packet loss rate of the link. In the fault set locating step, it includes two processes: constructing a set of suspected faults and locating faults based on Bayesian formula. The algorithm uses detection technology to obtain network performance through the collaboration of various management domains, and builds a Bayesian model and fault location based on network performance. Compared with existing research, this paper improves the performance of fault diagnosis through fault decomposition and management domain collaboration.

With the increase of network scale and the development of artificial intelligence technology, how to further realize autonomous large-scale fault diagnosis is an important and feasible research topic. In the next step, based on the research results of this article, we will explore a large-scale network fault autonomous diagnosis system based on artificial intelligence. Further improve the availability and convenience of the fault diagnosis system.

Acknowledgement. This work is supported by science and technology project from State Grid Jiangsu Electric Power Co., Ltd: "Technology Research for High-efficiency and Intelligent Cooperative Wide-area Power Data Communication Networks (SGJSXT00DDJS1900168)".

References

1. Lun, T., Yu, Z., Qi, T., et al.: 5G network slicing virtual network function migration algorithm based on reinforcement learning. J. Electron. Inf. Technol. **42**(3), 669–677 (2020)
2. Dusia, A., Sethi, A.S.: Recent advances in fault localization in computer networks. IEEE Commun. Surv. Tutor. **18**(4), 3030–3051 (2016)
3. Wu, B., Ho, P.H., Tapolcai, J., et al.: Optimal allocation of monitoring trails for fast SRLG failure localization in all-optical networks. In: Proceedings of 2010 IEEE Global Telecommunications Conference, Miami, USA, pp. 1–5 (2010)
4. Brodie, M., Rish, I., Ma, S., et al.: Active probing strategies for problem diagnosis in distributed systems. In: Proceedings of the 18th International Joint Conference on Artificial Intelligence, pp. 1337–1338. Acapulco, Mexico (2003)
5. Ogino, N., Kitahara, T., Arakawa, S., et al.: Decentralized Boolean network tomography based on network partitioning. In: Proceedings of 2016 IEEE/IFIP Network Operations and Management Symposium, Istanbul, Turkey, pp. 162–170 (2016)
6. Srinivasan, S.M., Tram, T.-H., et al.: Machine learning-based link fault identification and localization in complex networks. IEEE Internet Things J. **6**(4), 6556–6566 (2019)
7. Zegura, E.W., Calvert, K.L., Bhattacharjee, S.: How to model an internetwork. In: Proceedings of IEEE INFOCOM (1996)
8. Yu, M., Yi, Y., Rexford, J., Chiang, M.: Rethinking virtual network embedding: substrate support for path splitting and migration. ACM SIGCOMM CCR. **38**(2), 17–29 (2008)