An Intelligent Fault Location Approach Using Fuzzy Logic for Improving Autonomous Network

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***Abstract*—In recent years, Internet Service Providers (ISPs) are expected to enable various practical services. To meet the requirements of services, the infrastructure of networks has become more and more complex. In telecom networks, the complex infrastructure implies that it would be difficult to analyze the root causes and to locate the faults. In the telecom companies, network maintenance staffs need to spend a lot of time to trace the root cause and solve the network problems. An intelligent fault location approach allows ISPs to be cost-effective, and can assist humans in decision-making and increase automation. To automatically locate the faults, we apply both the Ant Colony Optimization (ACO) algorithm and fuzzy logic methods, and the main contributions of this paper are threefold: (1) we apply the pheromones of the ACO algorithm to quantify the risks that network devices might fail; (2) based on the risks, we leverage fuzzy logic, including the fuzzy relation matrix and the max-min composition method, to infer the fault location; (3) for improving autonomous network, we implemented and evaluated the proposed intelligent fault location approach using the real data in telecom networks.**

Keywords—automation, fault location, fuzzy logic, intelligent management, real data

I. INTRODUCTION

With the evolution of network technology, the telecom network architecture has become more and more complex. In the real world, the network architecture is composed of many heterogeneous devices. Because of the complex architecture, the Internet Service Providers (ISPs) need to pay a high cost to solve network problems. According to Sundaresan et al's study [1], it is expensive to diagnose/recover network failures, and each repair would cost about 9 to 15 dollars. If an ISP cannot locate the network fault correctly (and cannot dispatch the order to the correct unit for repair operations), it will lead to unnecessary transfers and thus increase additional costs. To reduce the operational costs and increase automation, one of the most important topics is fault location in telecom networks.

In the literature [2][3], fault location approaches can be divided into *learning-based* and *model-based* approaches. In learning-based approaches [4], they treat the whole network as a black box. To learn the relationship between the input and output data, they usually need the detailed network data, such as alarm events (as the input data) and the failure information (as the output). To locate the fault location more precisely, they may also need some additional components, such as expert systems, neural networks, and statistics models. These approaches require a lot of historical and labeled data for learning, e.g., machine learning and deep learning. However, because of complex and diverse devices in the real world, it is difficult to collect the long-term historical data and to label all the failure locations/nodes. In addition, because the network nodes and routing paths are always changing, how to update the learning models in real telecom systems would be a complicated and tough issue. On the other hand, compared with learning-based approaches, model-based approaches can describe the actual transmission paths and components using scripting or programming languages [5][6][7]. When a network failure happens, they can analyze and infer the fault location immediately. The advantage of the model-based approaches is that it is very intuitive, easy to process and verify. However, how to describe complex telecom networks by using model-based approaches is also a challenging issue.

In the field of fault location, many studies proposed the learning-based and model-based approaches, but few studies have focused on the practical and challenging issues in the complex telecom networks. This paper not only considers the advantages and drawbacks of fault location approaches, but also considers the practical and challenging issues in the real telecom systems. Specifically, the issues include (1) how to accurately locate the fault location when the telecom networks are complex, e.g., when some network information is missing; and (2) how to quickly locate the fault location in the real-time telecom systems. In this paper, we propose an intelligent fault location approach that uses both *Ant Colony Optimization (ACO)* [8] and *Fuzzy Logic* to infer the fault location in telecom networks. First, the concept of ACO is to search the best route by calculating pheromone concentration. We use ACO to derive the pheromone concentration of each network node, and it represents the health status of each node in the networks. In addition, we seriously consider the challenging issue: When some devices are disconnected (e.g., because of a power outage), ACO cannot work well because some data are missing. Hence, we further apply fuzzy logic to deal with the implementation issues. We use both the *fuzzy relation matrix* and *max-min composition* to diagnose the fault location in a short time. Even if not all data are available, the proposed intelligent fault location approach (based on ACO and fuzzy logic) can still calculate the probabilities of fault locations.

The rest of the paper is organized as follows. Section II describes the background information of ACO and fuzzy logic. Section III presents the network architecture and the proposed method (based on ACO and fuzzy logic). Section IV shows the experimental results through the real world system and data. Section V discusses the implementation issues and use cases. Finally, Section VI provides a conclusion.

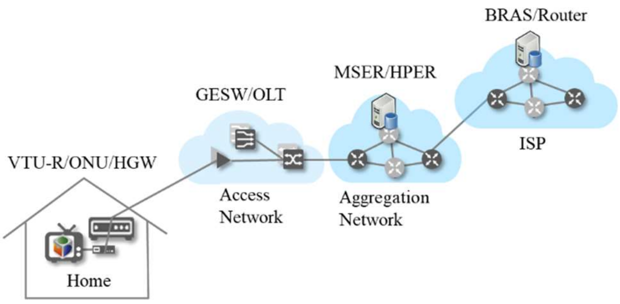

Fig. 1. The network architecture.

II. Background Information

In this paper, we proposed the novel intelligent fault location approach based on ACO and fuzzy logic. In this section, we provide the background information of ACO and fuzzy logic as follows.

A. *Ant Colony Optimization (ACO)*

The well-known ACO algorithm was first proposed in 1992 [9], and then it has been widely used in many fields [10]. Here we briefly describe the concept of ACO. To design an algorithm dealing with the route optimization problem, ACO utilizes the behavior of ant colony to find food. It was observed that when ants go out to find food, they would leave *pheromones* on their paths so that the pheromones can guide other ants to the destination later. In the early stage, the ant colony would move around randomly, and leave pheromones. When an ant encounters a pheromone-labeled path, it will determine whether to follow the original path or to find another path according to certain criteria. Note that more ants choose a path would result in more pheromones in the path. Then, the path may attract more ants so that the pheromone concentration could accumulate more quickly. On the other hand, if a path is chosen less, the pheromones will be volatilized over time so that the ants will not prefer to choose the path. After a period of time, the best path will appear.

B. *Fuzzy Logic*

The term fuzzy logic was introduced by L. A. Zadeh [11]. We briefly describe the concept of fuzzy logic as follows. Sometimes, it is difficult to digitize some concepts. For example, the weather is very hot; how many degrees is hot? Here is another example. The BMI is a standard to decide if you are fat or thin. However, some people may think that BMI should be in the range of 17-22, while doctors may suggest that BMI could be in the range of 18-24 (as a healthy person). In the above cases, fuzzy logic can help transform the concepts into digital numbers (with certain probabilities). Note that fuzzy logic simplifies some unimportant factors in its mathematical models so that it can be applied to root cause analysis for quick inference. For the fuzzy inference [12], there are four classic steps: (1) fuzzification; (2) creating the membership function depending on the rules given by experts; (3) executing the inference in a systematic way; and (4) defuzzification, that is the final inference results.

III. Methodology

A. *Network Architecture*

To support broadband network services, Fig. 1 shows a real example of network architecture. First, an ISP may provide a VTU-R (VDSL Transceiver Unit-Remote Terminal), an ONU (Optical Network Unit), or an HGW (Home Gateway) at a client's house (e.g., customer's home). Second, the home device can connect to the access network through OLT (Optical Line Terminal) and GESW (Gigabit Ethernet Switch) devices. Third, the access network links to the aggregation network composed of MSERs (Multiservice Edge Routers) and HPERs (High Performance Edge Routers). Finally, the network traffic can be routed to Internet routers via BRASs (Broadband Remote Access Servers).

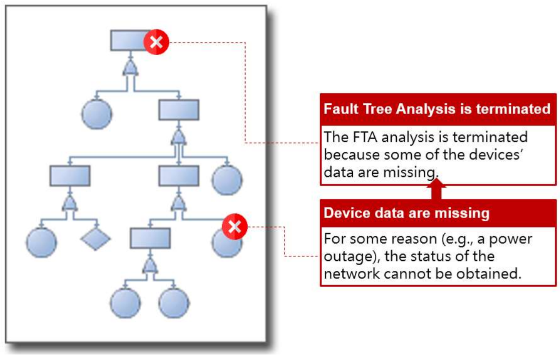

Fig. 2. An example of Fault Tree Analysis (FTA).

B. *Method Part I: Using ACO*

Under the network architecture, the fault locations can be detected by various approaches. However, few approaches can detect fault locations when some device information is missing, e.g., when a power failure occurs (it happens in the real telecom systems very often). For example, one of the well-known fault location approaches is Fault Tree Analysis (FTA) [13][14]. It is difficult for FTA to detect fault locations while the information (of certain devices) is missing. Therefore, we propose a novel approach (leveraging both the ACO and fuzzy logic) that can infer fault locations even when some devices are disconnected.

Specifically, in the telecom networks, there are thousands of devices (and millions of lines). If ISPs want to monitor network status in real time and to detect network failure quickly, the ISPs will need to tackle the following practical and difficult problems.

- Considering the cost, ISPs may use in-band network management over the links. In this case, the weakness of management is that the managed devices cannot operate well when the network connection is abnormal. In addition, when there are connections between the public networks and the private networks, the network management protocols would encounter the firewall problems and security issues.
- Before the network failure happens, it is difficult to detect a deterioration (of device status) in advance. In most cases, the ISPs can be aware of problems until the users report (i.e., complain about the problems).
- The network management systems are complicated. In many cases, it is difficult to implement a complex fault location approach in the existing systems.

Taking the practical issues into account, we notice that it is difficult for ISPs to monitor all the devices in real time. In other words, some devices are like in a black box, and the statuses of the devices cannot be known until a customer reports an error (to the ISP). In addition, according to practical experience, the majority of the network faults happen in the

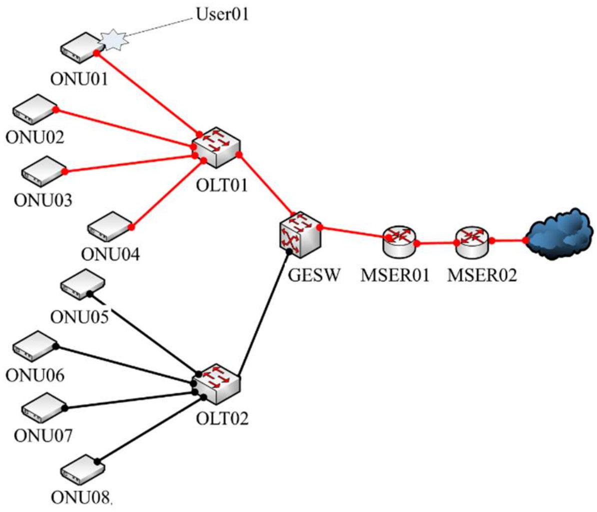

Fig. 3. The scenarios to explain the proposed method.

customer's home (e.g., VTU-R, ONU or HGW). This kind of failure has limited impact, and is easy to isolate and eliminate. Therefore, ISPs will focus on the center of the networks, i.e., the access and aggregation networks. As mentioned above, the networks are complex and composed of different devices. Unless network maintenance staffs have sufficient experience (and knowledge), they will try to find the fault location node by node. In this way, they may waste a lot of time, and it will take a long time for the network node (i.e., the device) to be repaired from a failure status. Subsequently, there were some methods (proposed in the literature [15][16]) that use the feedback (i.e., the response message) of customers to locate the fault nodes in a more efficient way.

Based on the report of customers, we propose the fault location approach using Ant Colony Optimization (ACO). The proposed method transforms the report messages into pheromone concertation (of ACO). To explain the proposed method, we describe different scenarios in Fig. 3 as follows.

In Scenario 1, the network failure is reported by the customer, i.e., User01. There is no other report (of network failure). Accordingly, we can infer that the network failure occurs in User01.

In Scenario 2, the network failure is also reported by the customer, i.e., User01. At the same time, the customers, who connect to ONU01, ONU02, ONU03, and ONU04, also report several network errors. Note that the routing path from the customer side to the ISP side is User01 → ONU01 → OLT01 → GESW01 → MSER01 → MSER02. Because ONU01, ONU02, ONU03, and ONU04 have the similar routing paths, we infer that the fault location is likely to occur in OLT01.

Scenario 2 points out that the concept of ACO can be used to infer the fault location(s). Specifically, in the proposed fault location approach, we assume that the routing paths in telecom networks can be transformed as the paths that the ants may choose in ACO. When a network failure is reported by a customer, its routing path can be regarded as the path that an ant walks through, and the ant would leave pheromones on the nodes (i.e., on the network devices of the path).

We explain how our proposed fault location approach calculates the pheromone concentration as follows. Let us consider Scenario 2. The pheromone concentration decreases exponentially with time and would drop to zero after t seconds.

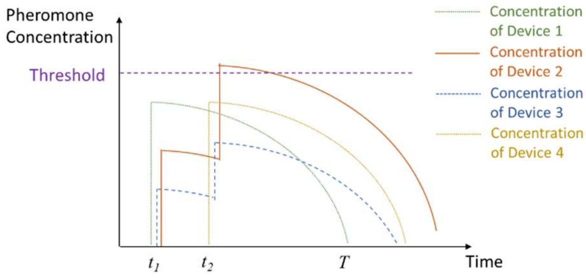

Fig. 4. Pheromone concentration with time.

For this phenomenon, two formulas are used in the proposed method:

$$f(\rho, \Delta t) = (\Delta\tau - \rho^{\Delta t} + 1)/\,\Delta\tau. \qquad (1)$$

Equation (1) is the decreasing function of pheromone concentration. In this function, $\Delta\tau$ represents the increasing variable of pheromone concentration when an ant walks through the node. On the other hand, ρ represents the decreasing variable of pheromone concentration, and Δt is the difference between the current time and the last time when the pheromone concentration was calculated.

$$\tau_i(t) = \left(\frac{\Delta\tau - \rho^{\Delta t} + 1}{\Delta\tau}\right)\tau_i(t - \Delta t) + \Delta\tau. \qquad (2)$$

Equation (2) is our pheromone-concentration function for fault location. In this equation, $\tau_i(t)$ represents the pheromone concentration of node i at time t. In addition, we consider the ratio of the pheromone concentration. If one node aggregates 100 customers, and 10 customers report network failures, the ratio will be 10/100=1/10 (10 out of 100 customers). At the same time, if another node aggregates 10 customers, and 4 customers report network failures, the ratio will be 4/10=2/5 (4 out of 10 customers). In this case, the former node has lower pheromone concentration (with a ratio of 1/10) than the latter node (with a ratio of 2/5).

The pheromone concentration with time is illustrated in Fig. 4. If numerous customers report network failures in the same routing path within a short time period, the pheromone concentration of these nodes (along the path) will accumulate rapidly. It implies that the probabilities of these nodes to be the fault location gradually increase. When the pheromone concentration exceeds a threshold (as shown in Fig. 4), the node is considered to be the fault location. Note that we implemented the proposed method in the real telecom system. In the network management system, when the threshold is reached, the fault location messages can pop up on the screen. In addition, the network maintenance staffs can query the information of this node (e.g., the probabilities), and then the ISP can solve the network problem efficiently

C. Method Part II: Using Fuzzy Logic

To improve efficiency, the proposed fault location approach not only uses ACO but also applies fuzzy logic, including the *fuzzy relation matrix* and *max-min composition*. As shown in Equation (3), a fuzzy relation matrix R is an m×n matrix. The column and row stand for the fault root cause and fault feature vector, respectively. The element $r_{i,j}$ represents the correlation between the fault feature x_i and root cause y_j. The larger value means the higher correlation between the fault feature and root cause [17][18]. Specifically, 0 means that they are not related, while 1 means the highest correlation.

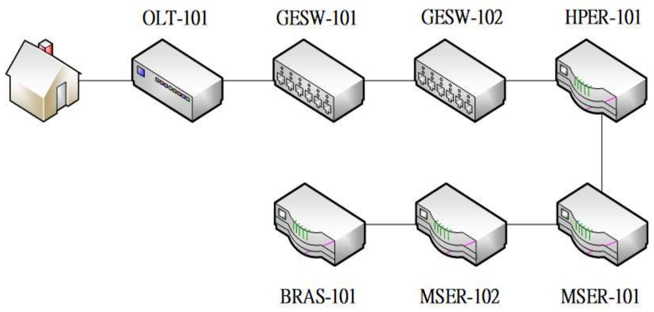

Fig. 5. A real example of a telecom network.

$$R = \begin{bmatrix} r_{1,1} & r_{1,2} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,1} & \cdots & r_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m,1} & r_{m,2} & \cdots & r_{m,n} \end{bmatrix} = \left[r_{i,j}\right]_{m\times n} \quad (3)$$

In the proposed fault location approach, the larger value of the element (of the fuzzy fault) means the higher probability that the network node is the root cause (i.e., the fault location). The value of each element (of the fuzzy relation matrix R) will directly affect the results of the fuzzy inference. Note that the fuzzy relation matrix R is generated by membership functions. The membership function(s) can be defined in different ways. In general, the appropriate membership function(s) can be defined based on experience (or expert advices). In addition, feedbacks from users can also improve the accuracy of the fault location inference.

To demonstrate how we use fuzzy logic in the proposed fault location approach, we take the real data in the fault report information system (from Chunghwa Telecom Co., Taiwan) as an example. The historical data are collected from 2018/11/01 to 2019/05/01. It is observed that 164 error reports of the FTTB (Fiber To The Building) services are caused by L3SWs (Layer 3 switches).

As shown in Fig. 5, an FTTB circuit route starts from OLT (Optical Line Terminal), GESWs (Gigabit Ethernet Switches), HPERs (High Performance Edge Routers), and then to MSERs (Multiservice Edge Routers). Finally, the route ends at the a BRAS (Broadband Remote Access Server), e.g., BRAS-101 in Fig. 5. We study on the nodes along the FTTB circuit route (to see if there is any pheromone concentration exceeds the threshold within an hour). As shown in Table I, we found some abnormal pheromone concentration of the network devices. For example, the pheromone concentrations of GESW-101, GESW-102, and HPER-101 were abnormally increasing and exceeding the threshold within an hour (before the circuit fault happened). Accordingly, we set it as 1/1 (one out of one) for these GESWs and HPERs (e.g., GESW-101, GESW-102, and HPER-101). On the other hand, there is no abnormal pheromone on other nodes; hence, we set it as 0/1 (zero out of one) for the other nodes. Because there are 164 circuits, we provide the calculation results in Fig. 6.

In Fig. 6, we transform the real numbers into fuzzy values. First, because the concentration of GESW is 0.402, the fuzzy value can be set as M (Medium). Second, because the concentration of HPER is 0.299, the fuzzy value can be set as ML (Medium Low). Third, the concentrations of OLT, MSER and BRAS are lower than 0.2 (and higher than 0.01); hence, we set their fuzzy values as L (Low).

TABLE I. A TABLE OF ABNORMAL PHEROMONE CONCENTRATION.

Device ID	Device Type	Pheromone Abnormal Time
BRAS-100	BRAS	2018/11/1 14:00
BRAS-101	BRAS	2018/11/1 14:30
GESW-099	GESW	2018/11/1 14:25
GESW-101	GESW	2018/11/1 14:30
GESW-102	GESW	2018/11/1 14:11
GESW-200	GESW	2018/11/1 14:59
GESW-500	GESW	2018/11/1 14:41
MSER-200	MSER	2018/11/1 14:22
HPER-101	HPER	2018/11/1 14:21
HPER-103	HPER	2018/11/1 14:20
HPER-200	HPER	2018/11/1 14:52

Evaluation Indicator	L3SW (Layer 3 Switch) Calculation by Ratio	L3SW (Layer 3 Switch) Calculation Results	Fuzzification
GESW Concentration	66/164	0.402	M
OLT Concentration	8/164	0.049	L
MSER Concentration	2/164	0.012	L
HPER Concentration	49/164	0.299	ML
BRAS Concentration	2/164	0.012	L
Probability (Fuzzification)	H (High Probability): >0.8	M (Medium Probability): 0.4~0.6	L (Low Probability): 0.01- 0.2
	MH (Medium High): 0.6~0.8	ML (Medium Low): 0.2~0.4	0: <0.01

Fig. 6. The L3SW pheromone concentration statistics.

Evaluation Indicator	FOT	VDSL	OLT	L2SW	L3SW	HPER	BRAS
GESW Concentration	L	L	L	ML	M	ML	L
OLT Concentration.	M	L	MH	L	L	L	L
MSER Concentration.	0	0	L	0	L	ML	M
HPER Concentration.	0	0	0	0	ML	L	L
BRAS Concentration.	0	0	0	0	L	ML	M

Fig. 7. A Fuzzy Relation Matrix.

As shown in Fig. 7, when we analyze other faults, such as FOT (Fiber Optical Transceiver), VDSL (Very-high-bit-rate Digital Subscriber Line), etc., we can apply the same approach and get the fuzzy relation matrix R. When some network errors occur, the proposed fault location approach can generate the fuzzy fault vector Y (by R calculating with the fault feature vector X). Finally, we can use Y to infer the probability of each fault location.

IV. RESULTS

A. Experimental Environment

We implemented the proposed intelligent fault location approach in the telecom information system. Our system currently manages many kinds of devices (with pheromone concentrations), including more than 282,000 GESWs. 3000 OLTs, 1000 MSERs, 100 HPERs, and 400 BRASs. The number of customers (i.e., the Internet and VPN end users) are more than 3,000,000. The backend system is developed by using Java (with Spring Framework), while the frontend user interface is implemented by using HTML, JavaScript, and JSP.

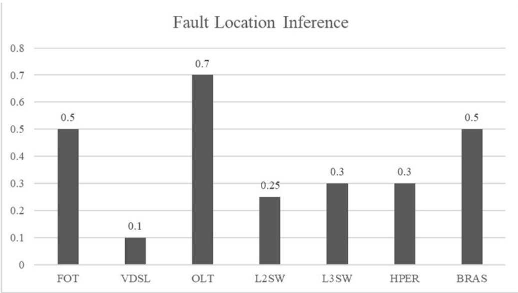

Fig. 8. User interface with fault location inference.

B. Experimantal Results

In the real system using the proposed fault location approach, the network maintenance staffs can use the user interface to query about the fault location probabilities (by typing the circuit identification number). Specifically, after using the proposed fault location approach, the user interface will provide the results (i.e., the fault location probabilities) as shown in Fig. 8. In addition, if the network maintenance staffs click one of the device types (e.g., GESW), the user interface will show which devices have pheromone concentrations exceeding the threshold. Accordingly, they can diagnose the fault location efficiently.

It is worth mentioning that the proposed fault location approach can significantly reduce the cost of ISPs. Before using the proposed method (i.e., using ACO and fuzzy logic), the fault report information system (in Chunghwa Telecom) usually takes more than 2 minutes to find the root cause of network failures. After using the proposed method, the network maintenance staffs only need to spend less than 1 minute to find the root cause (about 40 seconds in average). In Chunghwa Telecom (i.e., the largest ISP in Taiwan), the proposed method can save about 530,000 hours per year. Besides, the one-stop recovery rate (i.e., the fault report information system can dispatch the order to the correct location without any transfer) can be improved from 85% to 92.3% (in Chunghwa Telecom). Accordingly, the proposed fault location approach can effectively reduce the cost of ISPs.

V. Discussion

A. Implementation Use Cases

In this section, we discuss the implementation issues. To infer the fault location, we use both the ACO and fuzzy logic in the proposed method. Here, we provide two use cases. Specifically, we will show how to infer the fault location by using two different implementation methods.

We recall that the fuzzy fault vector Y can be generated by using the fuzzy relation matrix R and fault feature vector X. The fuzzy fault vector Y can indicate the probabilities of fault locations (from the highest probability to the lowest probablity). Let us give an example in this section. Suppose that there is a malfunction circuit passing 4 GESWs, 1 OLT, 3 MSERs, 4 HPERs, and 1 BRAS. We further suppose that the pheromone concentrations of 1 GESW, 1 OLT, 0 MSER, 3 HPERs, and 1 BRAS, exceed the threshold within one hour. In this case, we discuss how to infer the fault location (from the highest probability to the lowest probability). First, we defuzzify the fuzzy relation matrix R as shown in Fig. 7. Note that this step is to quantify the result of fuzzy inference into specific values. This is because the vague concepts (with ambiguities) cannot be applied to the general mathematical

$$Y = X \circ R =$$

$$[0.25 \quad 1 \quad 0 \quad 0.75 \quad 1] \circ \begin{bmatrix} 0.1 & 0.1 & 0.1 & 0.3 & 0.5 & 0.3 & 0.1 \\ 0.5 & 0.1 & 0.7 & 0.1 & 0.1 & 0.1 & 0.1 \\ 0 & 0 & 0.1 & 0 & 0.1 & 0.3 & 0.5 \\ 0 & 0 & 0 & 0 & 0.3 & 0.1 & 0.1 \\ 0 & 0 & 0 & 0 & 0.1 & 0.3 & 0.5 \end{bmatrix} =$$

$$\begin{bmatrix} 0.25 \wedge 0.1 & 0.25 \wedge 0.1 & 0.25 \wedge 0.1 & 0.25 \wedge 0.3 & 0.25 \wedge 0.5 & 0.25 \wedge 0.3 & 0.25 \wedge 0.1 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 1 \wedge 0.5 & 1 \wedge 0.1 & 1 \wedge 0.7 & 1 \wedge 0.1 & 1 \wedge 0.1 & 1 \wedge 0.1 & 1 \wedge 0.1 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 0 \wedge 0 & 0 \wedge 0 & 0 \wedge 0.1 & 0 \wedge 0 & 0 \wedge 0.1 & 0 \wedge 0.3 & 0 \wedge 0.5 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 0.75 \wedge 0 & 0.75 \wedge 0 & 0.75 \wedge 0 & 0.75 \wedge 0 & 0.75 \wedge 0.3 & 0.75 \wedge 0.1 & 0.75 \wedge 0.1 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 1 \wedge 0 & 1 \wedge 0 & 1 \wedge 0 & 1 \wedge 0 & 1 \wedge 0.1 & 1 \wedge 0.3 & 1 \wedge 0.5 \end{bmatrix} =$$

$$\begin{bmatrix} 0.1 & 0.1 & 0.1 & 0.25 & 0.25 & 0.25 & 0.1 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 0.5 & 0.1 & 0.7 & 0.1 & 0.1 & 0.1 & 0.1 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 0 & 0 & 0 & 0 & 0.3 & 0.1 & 0.1 \\ \vee & \vee & \vee & \vee & \vee & \vee & \vee \\ 0 & 0 & 0 & 0 & 0.1 & 0.3 & 0.5 \end{bmatrix} =$$

$$[0.5 \quad 0.1 \quad 0.7 \quad 0.25 \quad 0.3 \quad 0.3 \quad 0.5]$$

Fig. 9. An example of max-min composition.

operations. Hence, the fuzzy inference must be transformed into specific values. For example, if the network failure probability derived from fuzzy inference is high, it is necessary to transform it into a clear value, such as 0.9 (i.e., a high probability). Accordingly, each fuzzy element in R needs to be assigned a specific value in the process of defuzzification. Specifically, we set High probability H=0.9, Medium High probability MH=0.7, Medium probability M=0.5, Medium Low probability ML=0.3, Low probability L=0.1, and zero probablity equals 0.

B. Method I

Here, we use the above example to describe the first implementaion method. Fisrt, because there are 4 GESWs on the routing path and 1 of them has an abnormal pheromone concentration (i.e., its concentration exceeds the threshold), we can set the feature value as 1/4=0.25 (i.e., 1 out of 4). Second, there are 4 HPERs and 3 of them have abnormal pheromone concentrations. We set the feautre value as 3/4=0.75 (i.e., 3 out of 4). Third, there is 1 BRAS and its pheromone concentration exceeds the threshold. We set the feature value as 1/1=1 (i.e., 1 out of 1). Accordingly, we can set the fault feature vector X as follows: GESW=0.25, OLT=1, MSER=0, HPER=0.75, BRAS=1. That is X_1={0.25, 1, 0, 0.75, 1}. Then, we can use the defuzzification R and the fault feature vector X_1 to derive the fuzzy fault vector result Y_1={0.5, 0.1, 0.7, 0.25, 0.3, 0.3, 0.5} by using the fuzzy max-min composition [19]. We provide the detailed mathmatical operations in Fig. 9. Accordingly, the results show that the probabilities of fault locations (from high probability to low probablity) are OLT > BRAS = FOT > L3SW = HPER > L2SW > VDSL (i.e., 0.7 > 0.5 = 0.5 > 0.3 = 0.3 > 0.25 > 0.1). According to the fuzzy fault vector Y_1, network maintenance staffs can first check the statuses of the OLT, BRAS and FOT, and so on.

C. Method II

We use the same example as above to describe the second implementation method as follows. In the second method, we treat each network device as an independent unit. If an device fails, we set the probability as 1. Acoordingly, we can set the fault feature vector X_2={1, 1, 0, 1, 1}. By using the max-min composition, we can derive the fault vector result Y_2={0.5, .1, 0.7, 0.3, 0.5, 0.3, 0.5}. Subsequently, the probabilities of the fault locations (from high probability to low probability) are OLT> L3SW = BRAS = FOT> L2SW = HPER> VDSL (i.e., 0.7 > 0.5 = 0.5 = 0.5 > 0.3 = 0.3 > 0.1).

D. Use Both the Methods

As mentioned above (see Section V.B and Section V.C), the elements of the fuzzy fault vector *Y* may have the same value in the practical cases. For example, in Section V.C, the result of Method II shows that L3SW = BRAS = FOT. In this case, if OLT (with the highest probability) is not the fault location, ISPs will need to check the next three posible fault locations (i.e., L3SW, BRAS and FOT). Because they have the same probability, the network maintenance staffs will be confused. Taking the pratical issues into account, we will suggest that we can use different methods at the same time when designing the fault location system(s). For example, we can choose Method II (see Section V.C) as the primary indicator, while choosing Method I (Section V.B) as the secondary indicator. Because some elements in Method II have the same probability (i.e., L3SW = BRAS = FOT), we can furher check the probabilities of Method I (to make the best decision). Note that the different methods may have exclusive results (i.e., probablities). Accordingly, by using both the methods, the final result of the scenario in this section (i.e., Section V) is as follows: OLT > BRAS = FOT > L3SW = HPER > L2SW > VDSL.

VI. CONCLUSION

Because it is difficult to avoid network failures (caused by aging devices or human errors), it is an particularly important issue for ISPs to design the fault location systems. In this paper, we propose a novel intelligent fault location approach (for quick fault locating) to help ISPs reduce costs. The concept of the proposed method is as follows: If a large number of abnormal network circuits are inquired (i.e., users report faults), their routes may go through the same devices and the pheromone concentrations of these devices will increase abnormally; in this case, it may imply that these network devices have problems. Based on the concept, the proposed method is implemented in the telecom information system and can provide the priorities for network maintenance staffs to solve the network problems (i.e., locating network failures in order). Accordingly, the ISPs can deal with network failures in an autonomous and efficient way.

We use fuzzy logic in the proposed fault location approach. The proposed system will perform statistical analysis to generate the fuzzy relation matrix *R*. When a network fault occurs, the fault feature vector *X* will be generated; then, the proposed system will use fuzzy max-min composition for *X* and *R* to generate the fuzzy fault vector *Y*. According to the fuzzy fault vector *Y*, the network maintenance staffs can get the fault location probabilities (in order). Then, ISPs can effectively confirm whether the devices is abnormal.

In the future, there are many parts of the intelligent fault location system that can be improved. First, the fault location system could establish a feedback mechanism. Because the fault location function is based on historical data, it could adjust some settings. For example, to improve the accuracy of inference, the pheromone concertation threshold (of the fault location system) could be adjusted according to the users' feedback. Second, there is time difference between the time when the user reported the network failure and the time when the network failure occurred. For example, a network failure may occur in the morning, while the user may report the network failure in the evening (after the user comes home). Therefore, the fault location system could filter these kinds of samples to eliminate the time differences. This is one of the ways to improve the accuracy (of the fault location inference) of the system. Taking the practical issues and factors into account, we believe that researchers can further improve the fault location system in the near future.

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