Component Fault Location in Optical Networks based on Attention Mechanism with Monitoring Data

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Abstract *Targeting component fault location in optical networks, we propose a strategy based on attention mechanism, which includes three attention models. Simulation results indicate that the proposed strategy can achieve improvement of location accuracy by focusing on more critical monitoring data. ©2022 The Author(s)*

Introduction

In the foreseeable 6G and F6G, the traffic data of optical networks show an explosive growth trend, which puts forward higher requirements for network reliability. The inevitable network faults caused by aging or human error may result in massive data loss. Consequently, it is essential for network operators to accurately locate faults. A well-known approach is mining alert text information through deep learning [1-3]. However, it may rely heavily on historical experience and not be able to locate new faults. Recently, high-accuracy optical performance monitors (OPMs) and telemetry systems have been applied to network management [4]. They can provide precise and real-time physical-layer monitoring data (MD) to the network controller. Several studies locate faults by analyzing the correlation between MD [5-6]. Nevertheless, they usually locate a node fault only, not more precisely to a component in the node, which could lead to much additional cost of fault recovery. To accurately locate component faults, numerous OPMs are required to be deployed in optical networks for acquiring physical parameters of components. Due to the scale of such networks, the volume of MD is quite large, which poses a great challenge for fault location. Among MD, those near the faulty components are more critical to locate faults. Therefore, filtering out them from large-scale MD could be extremely helpful for achieving accurate component fault location.

Attention mechanism is an effective way to focus on the important information from massive input for the current task, which originates from the study of human vision [7]. Fig. 1(a) shows the comparison of introducing attention mechanism and not for data processing. When not introducing attention mechanism, all MD would be assigned a same weight. On the contrary, the introduction of attention mechanism can assign larger weight for more critical MD, assisting the fault location model to make more accurate decisions.

In this paper, we propose a fault location strategy based on attention mechanism (FL-AT) to locate component faults in optical networks with network-wide MD. We compare the performance of FL-AT with artificial neural networks (ANN) in partial telemetry scenarios [8]. Simulation results show that FL-AT can focus on the more critical MD and outperform ANN with respect to the accuracy of fault location.

Components and OPM Deployment

Fig. 1(b) shows the architecture of networks, where a hybrid optical-electrical switching node consists of an electrical switch (E-Switch) and a broadcast-and-select (B&S) reconfigurable optical add/drop multiplexer (ROADM) [9]. On the link, fibers are used for long distance transmission of signals. Line erbium doped fiber amplifiers (line-EDFAs) are placed between fiber spans to compensate attenuation. In the node, a signal is launched by a transmitter (Tx) and received by a receiver (Rx). Arrayed waveguide

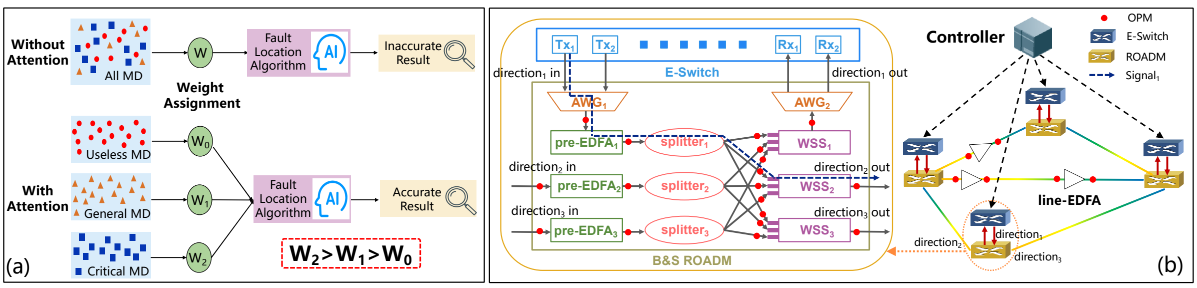

Fig. 1: (a) Comparison of introducing the attention mechanism and not for data processing; (b) Architecture of network with hybrid optical-electrical switching nodes.

gratings (AWGs) achieve signal (de)multiplexing. Pre-EDFAs are used to compensate component insertion loss. Splitters broadcast signals to each direction of ROADM and wavelength selective switches (WSSs) achieve flexible add/drop switching. We refer to the components on the link collectively as link components, and in the node as node components. OPMs are deployed at input and output ports of line-EDFAs, pre-EDFAs and WSSs. We also assume that each Tx and Rx is equipped with an internal OPM. In our work, the power data in MD are used to locate component faults.

Framework of FL-AT

Fig. 2 shows the framework of FL-AT, which adopts three attention models for data processing, namely long short-term memory network with attention mechanism (LAT), channel attention mechanism (CAT) and graph attention network (GAT).

Link Representation. We transform the power data on the link to a power sequence. Since these data are intrinsically correlated, LAT is implemented to extract sequence features [10], whose structure is shown in Fig. 2(b). We regard the input data as Key-Value pairs. Dot product is used to calculate the similarity between Key and Query for obtaining the weight corresponding to the Value. The larger the weight is, the more important the Value is. The output of LAT is obtained through a fully connected layer (FCL), whose input is the Value after weighted summation.

Node Representation. When passing through ROADMs, a signal would enter from one direction and depart from another. For instance, as shown in Fig. 1(b), signal$_1$ launched by Tx$_1$, enters ROADM from direction$_1$ through AWG$_1$, and leaves from direction$_2$ through pre-EDFA$_1$, splitter$_1$ and WSS$_2$. We view such a path as a channel. The power data of the OPMs it passes by could be regarded as a power sequence. There are plenty of channels like this in a ROADM. Therefore, we transform the power data in a node to a power matrix shown in Fig. 2(c), where each row denotes a power sequence. If the length of a sequence less than 5, e.g., direction$_2$ to direction$_3$, we employ -200 dB to fill it. CAT can create different score to each channel [11]. The larger the score is, the more important the sequence is. As shown in Fig. 2(d), we first adopt global pooling to squeeze the number of features of each sequence to 1. Then, it is followed by a dimension reduction layer, a dimension increase layer and a sigmoid activation to create a score for each channel. Next, scores are multiplied with the corresponding sequences. Finally, an FCL is used to complete the feature extraction.

Network Representation. We transform the network topology to the graph shown in Fig. 2(e) and take it as input of GAT. The solid nodes are initialized by the output of LAT and the hollow nodes are initialized by the output of CAT. For each node, GAT can generate different attention weights to it and its neighboring nodes via a graph attention layer [12]. The information of nodes with larger attention weight is aggregated more during node updating. In addition, multi-headed attention is introduced to help GAT perform better aggregation of node information.

At last, a fully connected neural network (FCNN) is applied to make decisions, which outputs a set of component fault probability values. The component with the highest probability is identified as the faulty one.

Simulation Results and Analysis

We evaluate FL-AT on a topology with 9 hybrid optical-electrical switching nodes and 24 unidirectional fiber links as shown in Fig. 2(a). The length of each fiber link is 100 km, which is composed of 5 20-km fiber spans and 4 line-EDFAs. We assume 3 wavelengths in a fiber, and each of them works at 10 Gbps. We simulate 100 static traffic demands whose source-destination and bandwidth are extracted from a real network operator in China, and the routing and wavelength assignment (RWA) follows the

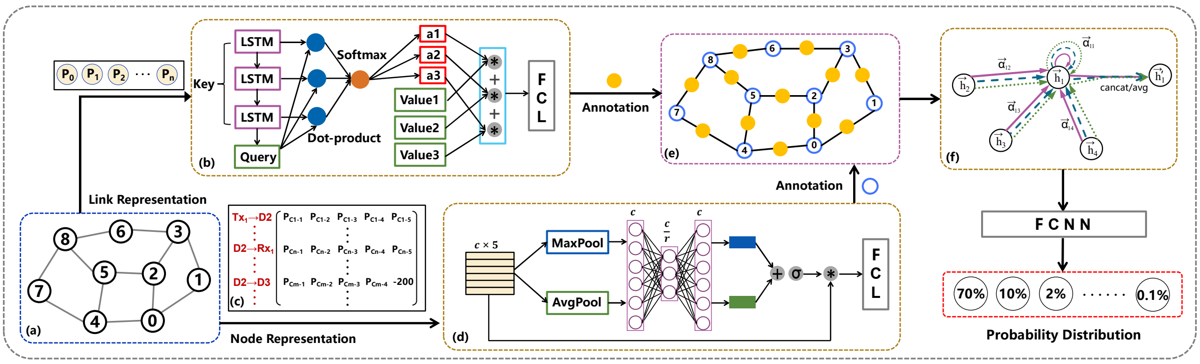

Fig. 2: Framework of FL-AT. (a) Network topology; (b) LAT for link power data processing; (c) Node power matrix; (d) CAT for node power data processing; (e) Input graph of GAT; (f) GAT for network-wide power data processing.

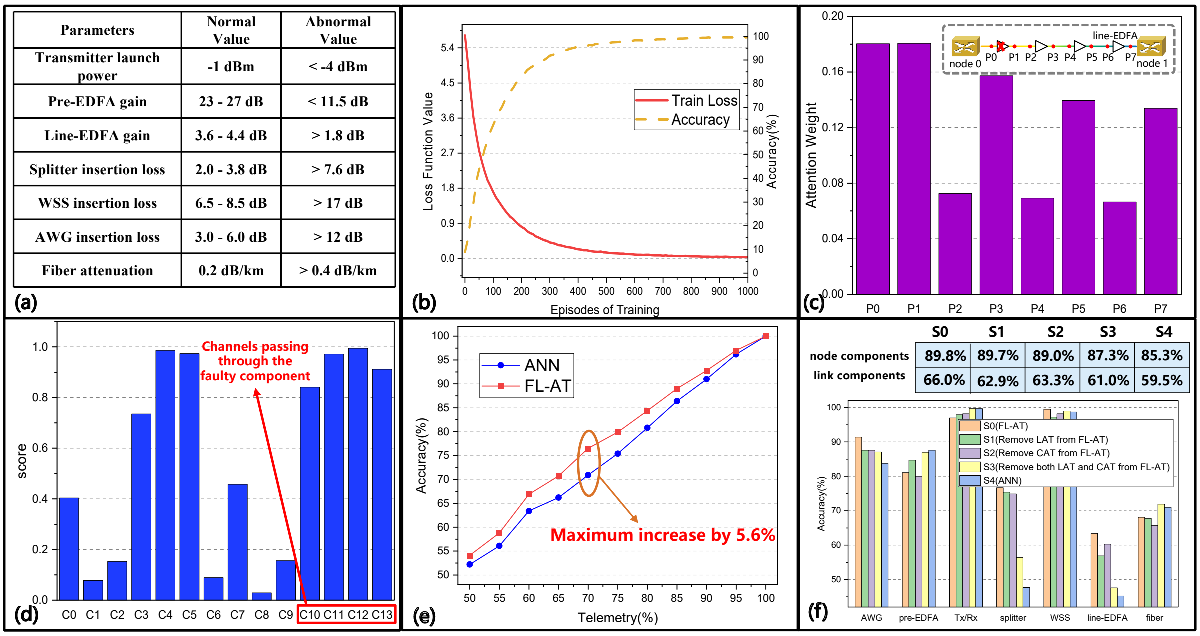

Fig. 3: (a) Component parameters; (b) Training process of FL-AT; (c) Attention weight of power data on the link from node 0 to 1; (d) Score of channels in node 7; (e) Accuracy vs. Telemetry; (f) The performance of five strategies when locating different component faults in 70% telemetry.

strategy of minimizing the number of wavelength-links (MinWL) [13]. There is a total of 386 components in the simulation network and their parameters are summarized in Fig. 3(a). We assume that a component is in fault when its parameter reaches abnormal value. In addition, we suppose that the receive power of a Rx will to -200 dB when it fails. Owing to the powerful robustness of optical networks, the probability of simultaneous fault of two or more components is quite low [14], so only single-fault scenarios are considered in our simulation. We generate 22,383 fault data, of which 80% are used for training and 20% for testing.

The training process of FL-AT is described in Fig. 3(b). The loss drops sharply at beginning, and eventually stabilizes at 0.006 after 850 epochs, simultaneously the accuracy reaches 100%. Fig. 3(c) shows the weights of the power data on the link from node 0 to 1 when locating a line-EDFA fault on it. The data near the faulty component (P0 and P1) are assigned larger weights by LAT. Fig. 3(d) displays the score of each channel in node 7 when locating a splitter fault in it. The channel passing through the faulty device acquires a relatively higher score from CAT. Thus, LAT and GAT can effectively focus on the critical MD of links and nodes respectively. We next present the location accuracy of FL-AT in partial telemetry scenarios, where only a certain ratio (i.e., 90%) of randomly selected MD from nodes and links, respectively, is available. The results of Fig. 3(e) demonstrate that FL-AT shows better performance than ANN and achieves a maximum improvement by 5.6% in 70% telemetry. Nonetheless, on the one hand, the enhancement effect is very slight in higher telemetry. That is because ANN can exhibit robust data mining capability when the datasets is complete. On the other hand, the improvement is also quite minimal in lower telemetry. The reason is that excessive data loss may severely impair the training effect of FL-AT, rendering it unable to notice the more critical MD. To verify the effect of each attention model on accuracy improvement, we remove LAT, CAT, both LAT and CAT from FL-AT respectively and test their performance of locating different component faults in 70% telemetry. We also test the performance of FL-AT and ANN. The results of Fig. 3(f) reveal that GAT makes a significant contribution to fault location. Despite the poor performance in locating some component faults (i.e., Tx), the introduction of LAT and CAT generally improves the accuracy of link and node component fault location, respectively.

Conclusions

In this work, we propose an FL-AT strategy for component fault location with analysis of large-scale MD. We verified its feasibility for improving fault location accuracy by focusing on the more critical MD. Our work achieves more precise fault location in optical networks, which can reduce much unnecessary cost of fault recovery.

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