Meta-Learning-based Failure Localization with Digital-Twin-enabled Multi-Mirror Models in Optical Networks

Ruikun Wang(1,2), Jiawei Zhang(1)*, Francesco Musumeci(2), Bojun Zhang(1), Zhiqun Gu(1), Massimo Tornatore(2) and Yuefeng Ji(1)

(1) State Key Lab of Information Photonics and Optical Communications, Beijing University of Posts and Telecommunications (BUPT), Beijing, China. *Corresponding author*: *zjw@bupt.edu.cn.
(2) Politecnico di Milano, Milano, Italy.

Abstract *We propose a novel meta-learning-based method with digital-twin-enabled multi-mirror models to realize inter/intra-node failure localization with only few samples. Experimental results reveal that it achieves satisfactory accuracy and adaptability regardless of the number of service requests, percentage of OPM and types of failure. ©2023 The Author(s)*

Introduction

Reconfigurable optical add/drop multiplexers (ROADMs) are currently evolving towards multi-degree architectures to support the growing traffic and a more flexible network connectivity [1,2]. Since a ROADM is composed of multiple devices, such as wavelength selective switches (WSS), a ROADM-based optical network includes both inter-node and intra-node links, where an inter-node link denotes the connection between nodes, while an intra-node link denotes the internal connectivity within a node. Hence, to achieve proper failure localization in ROADM-based optical networks, faulty devices should be identified in both inter-node and intra-node links. However, failure localization with inter-/intra-node has been shown to be a complex task [3].

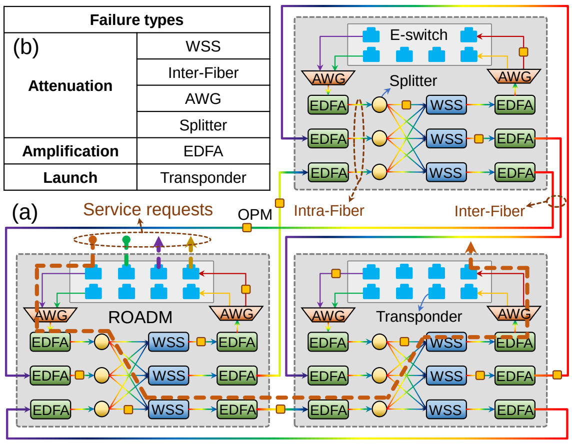
Machine Learning (ML) is a promising technique for failure localization [4-6], as ML can unveil the mapping between some monitored network features and the failure location based on historical data. Unfortunately, it is difficult to obtain sufficient failure ground-truth data in real optical networks, as optical performance monitors (OPMs) are not widely deployed and historical catalogue of failure data is not always comprehensive. Several approaches have been proposed to overcome these issues. For example, transfer learning allows to transfer models trained in networks with sufficient data (i.e., the source domain) to networks with insufficient data (i.e., the target domain) [7]; or generative adversarial networks (GANs) can expand the number of available training samples [8]. However, transfer learning performance heavily depends on correlation between source/target domain, while GAN needs lots of samples to train generator.

Recently, meta learning shows potential to model complex tasks with few samples thanks to its advanced model updating procedure [9]. By performing a "meta training" across similar tasks, a pretrained-model can be obtained, which then is adapted to a new task by fine-tuning it with few samples from the new task. However, obtaining a strong pretrained model usually requires many tasks. A possible solution is to build several mirror models via digital twin according to the parameters from the physical network [10-12]. These mirror models simulate various scenarios (e.g., different failures) to generate tasks.

In this study, we propose a meta-learning-based method to locate inter-/intra-node failures in ROADM-based optical networks. In this method, a digital twin is used to generate training tasks. We compare the proposed method with transfer learning and artificial neural network (ANN) without pretraining in a real testbed. Results show that meta learning quickly adapts to unseen scenarios with different number of service requests, percentage of OPM and failure types, and achieves satisfactory accuracy.

Network Scenario and Failure Model

Fig. 1(a) presents an example of a 3-node optical network with inter-/intra-node fiber links based on broadcast-and-selected (B&S) ROADMs. In the intra-node part, each electrical switch (E-switch)



Failure types	
Attenuation	WSS
	Inter-Fiber
	AWG
	Splitter
Amplification	EDFA
Launch	Transponder

Fig. 1: (a) Inter-/intra-node optical network with 3-node; (b) Failure devices.

is equipped with several transponders to send and receive traffic. ROADM consists of multiple devices, including arrayed waveguide grating (AWG), EDFA, splitter and WSS. These devices are connected via intra-node fiber links. In the inter-node part, inter-node fiber links support long distance transmission. Over this network architecture, multiple service requests are routed passing through different devices, and several OPMs (indicated as yellow squares) are deployed to monitor network status.

In optical networks, several devices may fail (e.g., due to aging or human activity), as shown in Fig. 1(b). Extra attenuation might arise due to failures in WSS, inter-node fiber links, AWG and splitters. Amplification failures occur when EDFAs cannot ensure sufficient amplification to signals. Launch failures are due to transponder malfunctioning, which may provide insufficient launch power. For sake of simplicity, in this work we focus on single-failure localization as multiple devices are unlikely to fail simultaneously.

Meta Learning for Failure Localization with Digital-Twin-enabled Multi-Mirror Models

Fig. 2 presents our scheme to obtain a meta learner for failure localization that generalizes to different failure scenarios.

Module 1: Generating training tasks by digital twin. First, we collect several parameters from the physical network shown in Fig. 2(a), including launch power of transponders, amplification gain of EDFA, and insertion losses of WSS, AWG, splitter and fibers. These parameters are used to build multiple mirror models as shown in Fig. 2(b), where each mirror model denotes a virtual scenario (i.e., including different number of services requests, OPM and failure types). These mirror models will provide different training tasks, as shown in Fig. 2(c), where the number of service requests ranges from 20 to 100 (step by 20), percentage of OPM ranges from 0.2 to 1.0 (step by 0.2), and index 0~6 denotes different combinations of failures. Hence, the total number of virtual scenarios used for meta training is 175 ($5 \times 5 \times 7$), and for each of them the failure locations are randomly selected. In this work, each mirror model corresponds to a training task $\mathcal{T}_i$, and it generates some samples. These samples are divided into support set and query set to pretrain and update the meta learner.

Module 2: Pretraining of meta learner based on training tasks. We take an ANN as a meta learner in Fig. 2(f). The ANN is denoted by a function f_ϕ with parameters ϕ. Fig. 2(e) shows the updating procedure of meta learning, where parameters ϕ_0 are randomly initialized. When adapting to a training task $\mathcal{T}_i$, meta learning will copy $f_{\phi_{i-1}}$ with a new function f_{θ_i} and then update f_{θ_i} using support set. The updating process is as follows:

$$\theta_i' = \theta_i - \alpha \nabla_{\theta_i} \mathcal{L}_{\mathcal{T}_i}^{s}(f_{\theta_i}) \tag{1}$$

where α is a learning rate and $\mathcal{L}_{\mathcal{T}_i}^{s}$ denotes cross-entropy loss of the support set in training task $\mathcal{T}_i$.

Meanwhile, we calculate the gradient for $f_{\theta_i'}$ based on query set, and then update meta learner $f_{\phi_{i-1}}$ with same gradient:

$$\phi_i = \phi_{i-1} - \beta \nabla_{\phi_{i-1}} \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}^{q}(f_{\theta_i'}) \tag{2}$$

where β denotes learning rate and $\mathcal{L}_{\mathcal{T}_i}^{q}$ is the cross-entropy loss of query set in training task $\mathcal{T}_i$.

Module 3: Finetuning of meta learner based on testing tasks. After pretraining with training tasks, we collect a test task from the physical network (see Fig. 2(d)) and use its support set to update meta learner by Eqn. (1). The finetuned learner will locate failures of inter- and intra-node based on the query set, and results are shown in Fig. 2(g). The above process is called Model Agnostic

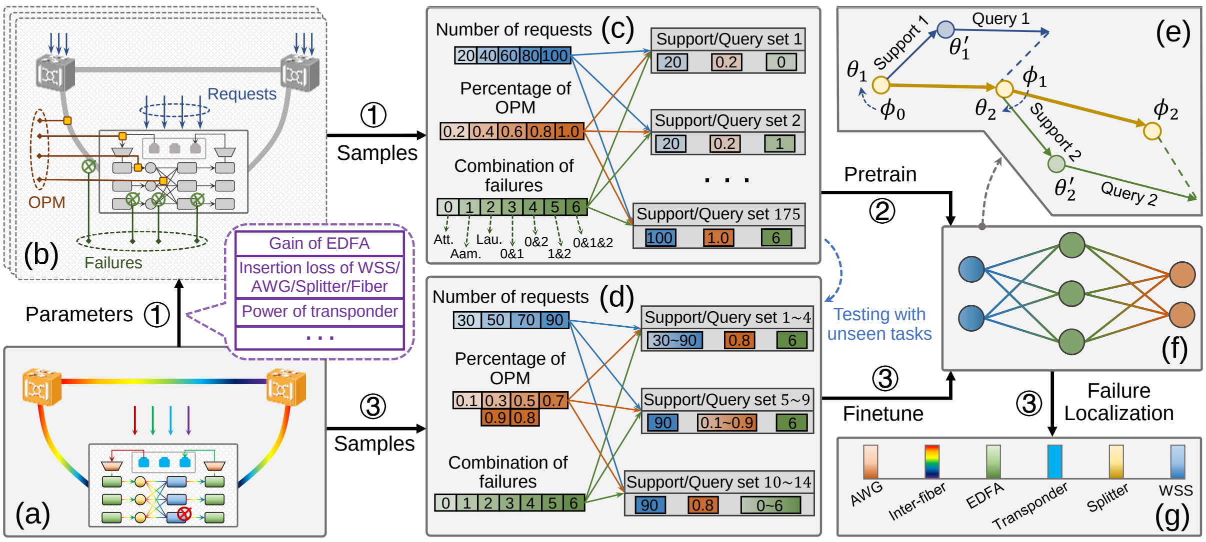


Fig. 2: Meta learning for failure localization with digital-twin-enabled multi-mirror models: (a) Physical network; (b) Mirror models; (c) Training tasks; (d) Testing tasks; (e) Updating procedure of MAML; (f) ANN-based meta learner; (g) Faulty devices.

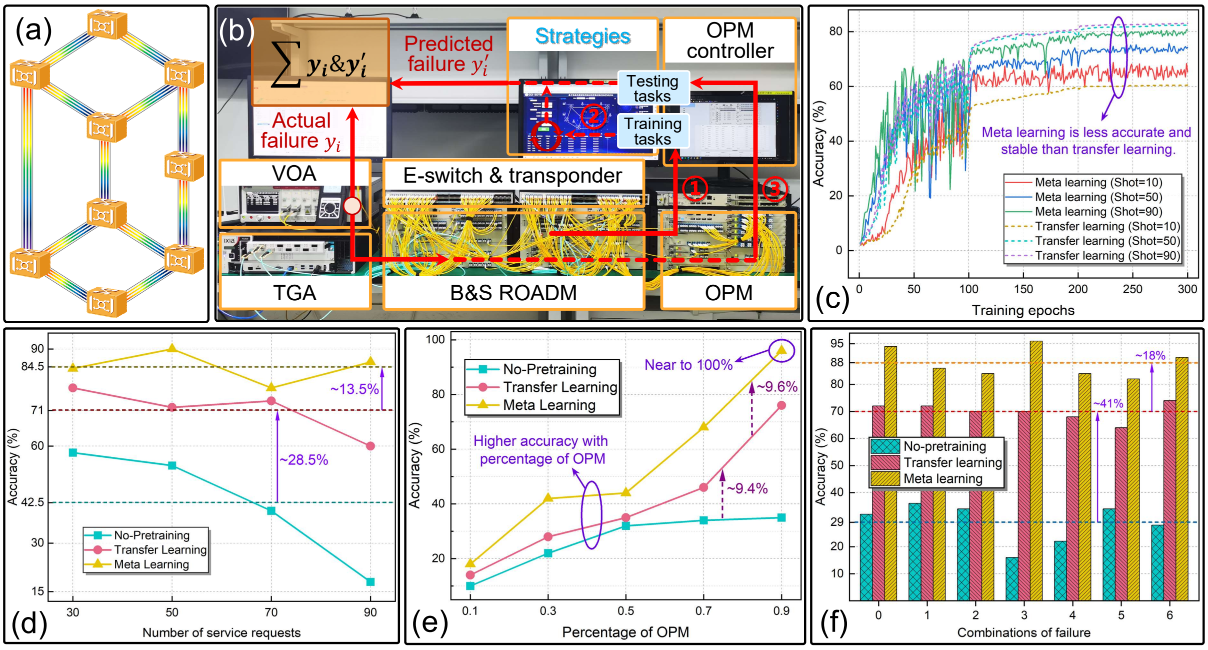


Fig. 3: (a) Topology; (b) Experimental procedure and testbed; (c) Pretraining accuracy vs. training epochs; (d) Testing accuracy vs. number of service requests; (e) Testing accuracy vs. percentage of OPM; (f) Testing accuracy vs. combinations of failure.

Meta Learning (MAML) [14].

Experimental Setup and Results

The proposed scheme is evaluated in the 9-node topology shown in Fig. 3(a). For training tasks, the detailed parameters are provided in our previous work [13]. Testing tasks are collected from a testbed shown in Fig. 3(b), where traffic generator and analysis (TGA) are connected with E-switches to inject live traffic, variable optical attenuator (VOA) simulates different failures, and OPMs monitor network status. Fig. 3(b) presents the experimental setup, which is consistent with Fig. 2. The meta learner is composed of ANN with 324×300×216 neurons, and the learning rates α and β are set to 0.001. We consider transfer learning and ANN without pretraining as the benchmarks. Transfer learning is pretrained with training tasks data and finetuned with testing tasks data, whereas no-pretraining method consists of training only using testing tasks data.

Fig. 3(c) shows pretraining accuracy of meta learning and transfer learning under different training epochs (*nb*: each epoch has 175 tasks), where shot denotes the number of samples in each task. It can be observed that accuracy increases with the number of shots. In addition, transfer learning is more accurate and stable than meta learning. The reason is that transfer learning minimizes the total loss while meta learning focuses on stronger adaptability. Shot is set to 50 in the following experiments. Fig. 3(d) shows testing accuracy for increasing the number of service requests, where percentage of OPM is 0.8 and failure index is 6. Meta learning achieves higher accuracy followed by transfer learning and no-pretraining due to its efficient pretraining. Fig. 3(e) shows testing accuracy under different percentage of OPM, where the number of service requests is 90 and failure index is 6. It shows that adding OPMs is beneficial to improve accuracy, but it will increase the cost of CAPEX. Moreover, meta learning also achieves higher accuracy than benchmarks. Finally, we present testing accuracy under different combinations of failure in Fig. 3(f), where the number of service requests is 90 and percentage of OPM is 0.8. The results indicate that meta learning improves accuracy of 18% and 59% on average compared to transfer learning and no-pretraining, respectively. The failure types do not greatly affect accuracy since different failures all result in abnormal monitoring values, which is easily analysed by ML.

Conclusion: We have proposed a novel meta-learning-based method with digital-twin-enabled multi-mirror models to locate failures of inter-/intra-node. It improved accuracy over 9% on average comparing with transfer learning under different number of service requests, percentage of OPM and types of failure. This approach can accurately locate failures with limited data.

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