Digital-Twin-assisted Meta Learning for Soft Failure Localization in ROADM-based Optical Networks [Invited]

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Reconfigurable Optical Add/Drop Multiplexer (ROADM) nodes are evolving towards high-degree architectures to support growing traffic and enable flexible network connectivity. Due to the complex composition of high-degree ROADMs, soft failures may occur between both inter- and intra-node components, like Wavelength Selective Switches (WSSs) and fiber spans. The intricate ROADM structure significantly contributes to the challenge of localizing inter-/intra-node soft failures in ROADM-based optical networks. Machine Learning (ML) has shown to be a promising solution to the problem of soft-failure localization, enabling network operators to take accurate and swift measures to overcome such challenge. However, data scarcity is a main hindrance when using ML for soft-failure localization, especially in the complex scenario of inter- and intra-node soft failures. In this work, we propose a digital-twin-assisted meta-learning framework to localize inter-/intra-node soft failures with limited samples. In our proposed framework, we construct several mirror models using a digital-twin of the physical optical network and then generate multiple training tasks. These training tasks serve as pre-training data for the meta-learner. Then, we use real data for fine-tuning and testing of the meta-learner. The proposed framework is compared with Rule-based Reasoning method, Transfer-Learning-based method and Artificial Neural Networks (ANNs)-based method with no-pre-training. Experimental results indicate that the proposed framework improves localization accuracy by over 15%, 33% and 54%, on average, compared to benchmark approaches, respectively.

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1. INTRODUCTION

In current optical networks, Reconfiguable Optical Add/Drop Multiplexers (ROADMs) play a fundamental role in enabling dynamic and flexible wavelength routing. As traffic continues to grow, ROADMs are evolving towards high-degree architectures to provide more flexible network connectivity [1, 2]. A higher-degree ROADM implies a higher number of optical components such as Wavelength Selective Switches (WSSs) and amplifiers inside the ROADM node, i.e., in the intra-node network, and between the ROADM nodes, i.e., in the inter-node network. Due to the complex composition of ROADM-based optical networks, soft failures[1] may occur in various components and cause partial degradation in performance [3, 4]. In the context of high-degree ROADM-based optical networks, soft-failure localization implies considering both inter- and intra-node networks, aiming to provide accurate predictions for the network operators who can then take swift actions to minimize performance degradation.

Soft-failure localization is typically modeled as a multi-class classification problem, where each class denotes a soft-failure location, e.g., the location of a specific WSS within a ROADM. Machine Learning (ML) has been shown to be a promising solution for soft-failure localization as it allows to map historical data of some monitored features to the location of the soft failures [5]. Most of the existing literature on ML-based soft-failure localization and identification assumes a vast availability of historical data [6, 7]. In reality, data scarcity still represents one of the main obstacles to practical deployment of ML-based approaches for soft-failure localization and identification, as it is difficult to collect sufficient soft-failure ground-truth data from high-degree ROADM-based optical networks due to the lack of a widespread deployment of Optical Performance Monitors (OPMs), and to the fact that failure data is unlikely to comprehensively represent all failure scenarios [8].

[1]Unlike hard failures, which typically result in a complete loss, e.g., a fiber break, soft failures might degrade network performance without causing total outages, such as extra attenuation of WSSs and insufficient gain of amplifiers.

Several alternatives can be adopted to address data scarcity in the context of ML-based soft-failure localization. Recently, meta-learning has demonstrated potential in modeling complex classification tasks with only a few samples thanks to its advanced model updating procedure [9–11]. By leveraging meta-training across many training tasks that encompass diverse problems or domains, meta learning allows to obtain a pre-trained ML model that can then be rapidly adapted to new situations by fine-tuning it with a limited amount of additional samples.

In this paper, we propose a digital-twin-assisted meta-learning framework for soft-failure localization. The digital twin builds several mirror models based on the collected parameters from physical optical networks [12–14], and simulates different virtual scenarios (e.g., various soft-failure types) to generate many training tasks and samples. These samples are used to pre-train the meta-learning model. Then, the pre-trained model is fed with a portion of the real network data to fine-tune the meta-learning model. Once the model is fine-tuned, its performance is tested on previously unseen data.

In this study, we extend our preliminary analysis presented in [15], and propose a digital-twin-assisted meta-learning framework to localize inter-/intra-node soft failures with limited real samples. The main novel contribution of this paper with respect to [15] can be summarized as follows:

1) This paper extends the description of inter-/intra-node soft failures and introduces a new discussion on their effects. Moreover, we introduce a new soft-failure categorization to investigate the effect of different soft failures to optical networks.

2) We introduce a new method to simulate different soft failures via digital-twin-enabled mirror models to be used to generate various training tasks.

3) The proposed framework is compared against a new baseline, i.e., a rule-based reasoning method. Moreover, we evaluate these methods using a larger dataset than in the previous work [15] and present extensive numerical results.

The rest of this paper is organized as follows. Section 2 overviews related works regarding existing soft-failure localization methods with few samples. Section 3 introduces the considered network scenario and our proposed inter-/intra-node failure categorization for soft-failure localization. Section 4 describes the proposed digital-twin-assisted meta learning framework. In Section 5, the experimental setup and results are provided and discussed. Finally, Section 6 concludes this paper and discusses possible lines of future research.

2. RELATED WORKS

ML has been used extensively in the context of optical network management to address problems such as traffic prediction [16], Quality-of-Transmission estimation [17], and Soft-Failure management [18]. While the adoption of ML for optical-network management is on the rise, it is well known that ML models are only as good as the data they are trained on. Regarding soft-failure localization, there have been several approaches developed in recent years that aim to address the issue of limited training data. In the following, we describe some of the most relevant works and highlight the differences to our proposed approach. In particular, we describe the use of 1) Data Augmentation, Generative Adversarial Networks and Active Learning, 2) Semi-Supervised ML, 3) Fault Injection, and 4) Transfer Learning to address the issue of data scarcity.

Data augmentation increases the diversity of a dataset by creating modified or synthetic versions of the existing data [19]. It provides more varied training samples without collecting new data. A data augmentation technique, based on variational autoencoders, was proposed for failure management with the aim of both increasing the amount of data and enhancing their quality [20], including soft failures as filter tightening, filter shift and attenuation. The authors presented significant performance improvement of 37.56% and of 66.5% in terms of reduction in ML training times for soft-failure detection and identification, respectively. Ref. [21] proposed a data-augmented Bayesian network for node failure prediction, obtaining good accuracies.

Generative Adversarial Network (GAN) is an another efficient approach to address data scarcity, since it utilizes adversarial training to generate synthetic data and helps augment limited samples for more robust model training. While GANs have shown to perform very well when dealing with image data [22], the efficacy of GANs in the context of soft-failure management is still under investigation. Ref. [23] proposed a GAN-based framework to extend training samples for soft-failure detection and identification. The GAN model was trained with several normal samples for soft-failure detection, and few failure samples are included in soft-failure identification. The identification of soft failures achieved an accuracy exceeding 95%. Unfortunately, training GANs models is a time-consuming procedure that also requires a substantial amount of training data. Besides, *Active Learning* is well-suited for situations featuring abundant data, aiming to identify which data are more informative. This method significantly optimizes datasets by strategically prioritizing the acquisition of new data points that are most informative or challenging for an ML model [19]. However, active learning has been mainly studied for Quality-of-Transmission estimation [24, 25].

Semi-Supervised ML provides a new perspective to solve data scarcity by efficiently jointly exploiting limited labeled data and a vast amount of unlabeled data. Ref. [26] presented a value-imputation and mask-estimation (VIME) based semi-supervised ML framework for failure detection under limited labeled data. This method improves the performance of failure detection by using a large amount of unlabeled data, and achieved detection F1 score and accuracy of 0.951 and 0.949, respectively. Ref. [27] investigated failure detection based on semi-supervised anomaly detection algorithm, which only used normal data in training phase and used just few failure data (< 3%) during the validation phase. The proposed solution obtained detection accuracy of 96.8% and F1 score of 0.9224. However, these solutions might exhibit sensitivity to labeling errors, and the design and tuning procedure proves to be challenging as well.

Fault Injection consists in intentionally introducing real faults into networks to assess their resilience and collect failure data. While fault injection is a valuable technique to address data scarcity, it might encounter resistance from optical network operators due to the unpredictable risks it introduces. There are some research works about fault injection in edge computing systems [28], network applications [29] and ML models [30]. However, fault injection remains scarcely utilized in practice in optical networks.

Transfer Learning (TL) is an effective method to obtain highly-accurate ML models with limited samples. The concept of TL is to leverage knowledge gained from a source domain (e.g., a network or a set of networks), which typically has abundant data, and then transfer that knowledge to improve performance on a target domain (e.g., a network with scarce data). Ref. [31] studied domain adaptation and TL for failure detection and identification across different lightpaths leveraging real optical

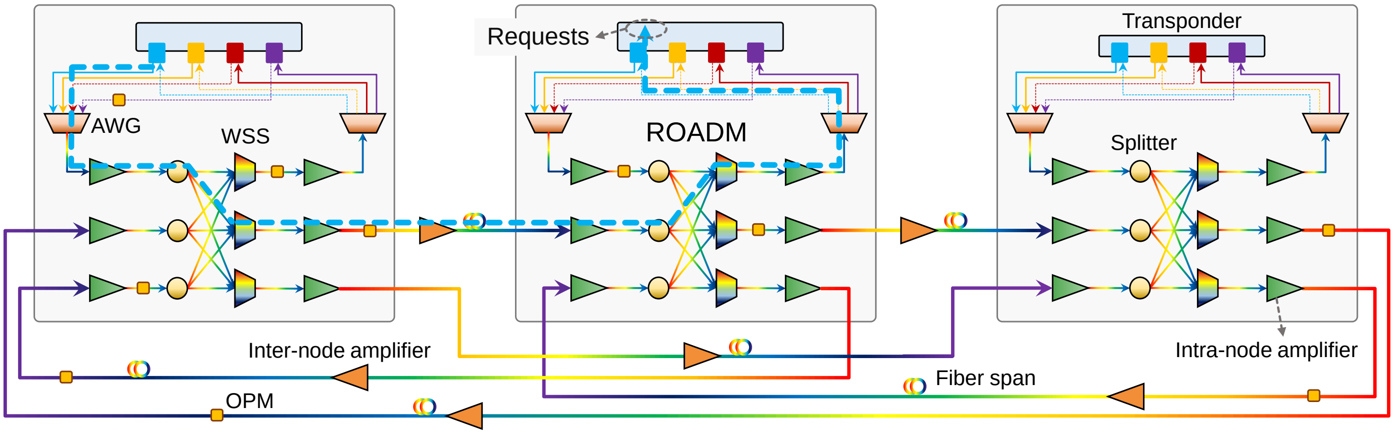

Fig. 1. ROADM-based inter- and intra-node optical networks.

Table 1. Soft failures of inter-/intra-node components and corresponding effects.

Soft-Failure Types	Soft-Failure Components	Soft-Failure Effects
Amplification	Inter-/intra-node Amplifiers	Insufficient amplification (0% - 100% of normal amplification gains)
Attenuation	Fiber spans, Splitters, WSSs, AWGs	Extra attenuation (100% - 200% of normal attenuation values)
Launch	Transponders	Insufficient launch power (0% - 100% of normal launch powers)

SNR data from an optical testbed. Experimental results show that 20% and 4% - 5% points of accuracy increase can be obtained for failure detection and cause identification, respectively. A similar approach has been adopted in Ref. [32], where TL across different lightpaths is used for failure detection and localization. Moreover, TL is utilized to learn across tasks, i.e., transferring models from the soft-failure localization task to the soft-failure identification task and vice-versa. Numerical results show that cross-task failure detection and localization reaches up to 12% or 25% improvement when considering failure localization and detection, respectively. However, TL performance significantly depends on correlation between source domain and target domain, presenting a limitation to its scalability.

All these existing ML-based methods encountered limitations such as susceptibility to domain shift, time-consuming training procedure and unpredictable risks, etc. These limitations raise concerns about the generalizability and reliability.

Meanwhile, we summarize several existing works of soft-failure localization using methods other than Machine Learning. Ref. [33] localized failures through the analysis of routing matrices and alarm vectors based on monitoring data from coherent transponders. Ref. [34] presented a fault propagation model based on low-density check matrices to solve fault-location problems, and this model was validated in the communication network of the China Southern Grid. Ref. [35] experimentally demonstrated a soft-failure monitoring system, in which the power features were monitored to localize soft failures. However, these strategies have the limited ability to adapt to evolving optical systems and environments, as they rely on pre-defined rules and heuristics.

3. NETWORK SCENARIO AND SOFT-FAILURES

Fig. 1 illustrates an example of a ROADM-based inter-/intra-node optical network, wherein ROADM nodes are constructed using a cost-effective broadcast and selected (B&S) architecture. In this architecture, splitter is used to broadcast incoming signals, which reduces the number of required WSSs. In the intra-node network, each ROADM node is composed of multiple components: 1) Transponders are used to send and receive live traffic; 2) Arrayed Waveguide Gratings (AWGs) are responsible for (de)multiplexing different wavelengths; 3) WSSs are responsible for dynamically routing wavelengths to different ports or directions within the ROADM node; 4) Splitters are responsible for dividing incoming optical signals into multiple output paths, allowing for signal distribution to various degrees within the node; 5) Amplifiers within ROADMs serve to amplify optical signals to compensate the losses due to other intra-node components. The above components are connected via intra-node fiber links. In the inter-node network, several inter-node fiber spans support long distance transmission between different ROADM nodes, and inter-node amplifiers maintain signal integrity. Based on this network architecture, multiple service requests are routed passing through different inter- and intra-node components. For example, one service request is illustrated by blue dotted lines in Fig. 1. In this network scenario, signal power values are monitored via OPMs to localize soft failures. We consider both sides of each component as candidate positions for placing OPMs. In real deployment, several OPMs (indicated as yellow squares) are typically deployed [36], but not necessarily all the candidate locations are equipped with OPMs. The power features collected at OPMs can be used to localize soft failures based on different methods.

Soft failures within ROADM-based optical networks stem from multiple factors, encompassing environmental conditions, device aging and human activity. As shown in Table 1, all soft failures are divided into three categories according to their effects. *Amplification* soft failures emerge when inter-/intra-node amplifiers fail to maintain sufficient gains to compensate for the losses of other components. These soft failures lead to actual amplification levels that fluctuate between 0% and 100% of the anticipated normal amplification gains (i.e, 100 %). *Attenuation* soft failures contribute to additional signal loss, affecting different components like fiber spans, splitters, WSSs and AWGs. The extra attenuation ranges from 100% to 200% of normal values (i.e, 100%). *Launch* soft failures are due to transponder malfunctioning, potentially providing insufficient launch power. The transponder is deemed as a soft-failure component when its launch power falls below the normal value expected. In this work, OPMs are strategically deployed to monitor real-time network status. We focus on single-failure localization as multiple components are unlikely to fail simultaneously.

We model the soft-failure localization in ROADM-based optical networks as a supervised multi-classification problem, where each class denotes a soft-failure location, e.g., one specific location of an AWG. The optical powers collected from OPMs are used as input features, while soft-failure locations are encoded as output labels. In the next section, we propose a new framework to find the mapping between many input features and single soft failure-location with only few samples.

4. DIGITAL-TWIN-ASSISTED META LEARNING

This section details a digital-twin-assisted meta learning framework to localize soft failures with only limited real samples. We first describe how to obtain multiple training tasks and samples based on digital-twin-enabled mirror models. Then, meta learner is pre-trained with multiple training tasks and samples. Subsequently, the pre-trained meta learner will be fine-tuned and tested based on the collected real samples.

A. Digital Twin for Generating Training Tasks

Traditional supervised learning typically focuses on a single task, modeled using a fixed dataset, where *training samples* are regarded as the fundamental units for model training. Instead, as depicted in Section 1, in meta-learning, *training tasks* and *testing tasks* (each comprising multiple samples) are regarded as the basic units for the learning procedure. In this subsection, we show how to obtain multiple training tasks and samples using a digital twin. The detailed pseudocode is presented in Algorithm 1.

Digital twin is a new simulation technology to build models that mirror physical optical networks, also referred to as mirror models. Digital twins collect several physical parameters from a physical optical network, and hence can simulate and predict different systems evolutions, providing crucial assistance for physical optical networks. In our work, we build several mirror models via the digital twin to simulate various virtual soft-failure scenarios. Thus, these virtual failure scenarios can provide sufficient training tasks and samples to train a meta learner, i.e., meta-learning models. We take several parameters as the inputs: 1) Physical parameters are collected from the physical optical network, including launch power and capacity of transponders, amplifier gains of inter-/intra-node amplifiers, as well as insertion losses of AWGs, splitters, WSSs and fiber spans. 2) Set $\boldsymbol{S}$ denotes the service requests, including source/destination pairs and capacity demands. 3) Set $\boldsymbol{P}$ denotes different OPM deployments. 4) Set $\boldsymbol{F}$ denotes different combinations of soft-failure types. 5) Set $\boldsymbol{K}$ denotes the training samples for each training task. We first construct a general mirror model according to the collected parameters as outlined in Line 1, ensuring the mirror model without any service requests, OPMs and soft failures. The next step involves generating various different mirror models to simulate distinct network scenarios, expanding upon the foundation established by the general mirror model. In this step, we make a copy of the general mirror model, and select s service requests, a deployment of OPMs such that a percentage p of the maximum number of OPM is deployed, and combination f of failure types (shown in Line 2 and 3). We consider that a combination includes single or multiple failure types, e.g., only amplification failure, or attenuation and launch failures. These OPMs will be deployed using the uniform strategy referenced in Line 4. The uniform strategy arranges all candidate OPM positions into a sequence, and then selects certain positions at fixed intervals from this sequence to deploy OPMs, where the interval is calculated according to percentage p [36]. Service requests are generated with random source/destination pairs and capacity demands, and then routed into the copied mirror model generated in Line 5. Subsequently, $|\boldsymbol{K}|$ training samples are generated for current mirror model (Line 6). Each training sample consists of several input power values monitored by OPMs and one soft failure location. Lines 7 and 8 show how to obtain them, i.e., following the soft-failure categorization presented in Table 1, we randomly select a soft failure location with type f, and calculate the monitoring value for each deployed OPM. In meta-learning, the dataset of each training task is divided into a support set and a query set, where the support set helps the meta learner generalize learning across training tasks, and query set evaluates the meta learning's performance on unseen data. Thus, we equally divide the dataset of each training task into a support set and a query set to pre-train and update the meta learner, as depicted in Line 9. The above procedure is repeated until we obtain total training tasks and samples (shown in Line 10 and 11).

Algorithm 1. Digital-twin-enabled mirror models to generate training tasks and samples.

Input: 1) physical parameters; 2) set $\boldsymbol{S}$ of service requests; 3) set $\boldsymbol{P}$ of possible OPM deployments; 4) set $\boldsymbol{F}$ of combinations of failure types; 5) set $\boldsymbol{K}$ of training samples for each training task
Output: training tasks $\mathcal{T}$ and samples

1: build a general mirror model according to the collected physical parameters
2: **for** $s \in \boldsymbol{S}$, $p \in \boldsymbol{P}$ and $f \in \boldsymbol{F}$ **do**
3: replicate the general mirror model as a virtual scenario, i.e., training task $\mathcal{T}_i$ ($\mathcal{T}_i \in \mathcal{T}$)
4: deploy OPMs with percentage p into the virtual scenario
5: generate s service requests and route them into the virtual scenario
6: **for** training sample $k_{\mathcal{T}_i} \in \boldsymbol{K}$ **do**
7: randomly select a soft failure location with type of f, and the failure effect is based on Table 1
8: calculate monitoring values for each placed OPM
9: divide all training samples ($k_{\mathcal{T}_i} \in \boldsymbol{K}$) into support set and query set
10: take support set and query set to get training task $\mathcal{T}_i$
11: **return** training task $\mathcal{T}$ and corresponding samples

To simplify comprehension of Algorithm 1, we illustrate an example of the mirror models for simulating soft failures in Fig. 2. Multiple parameters are used to build the general mirror model, including launch power of -1 dBm and capacity of 10 $Gbps$ for transponders, inter-/intra-node amplifier gains of 10 dB and 20 dB, and insertion losses of 5 dB, 6 dB, 3 dB and 0.2 dB/km for AWGs, WSSs, splitters and fiber spans, respectively. Besides, one service request is routed (indicated as blue dashed

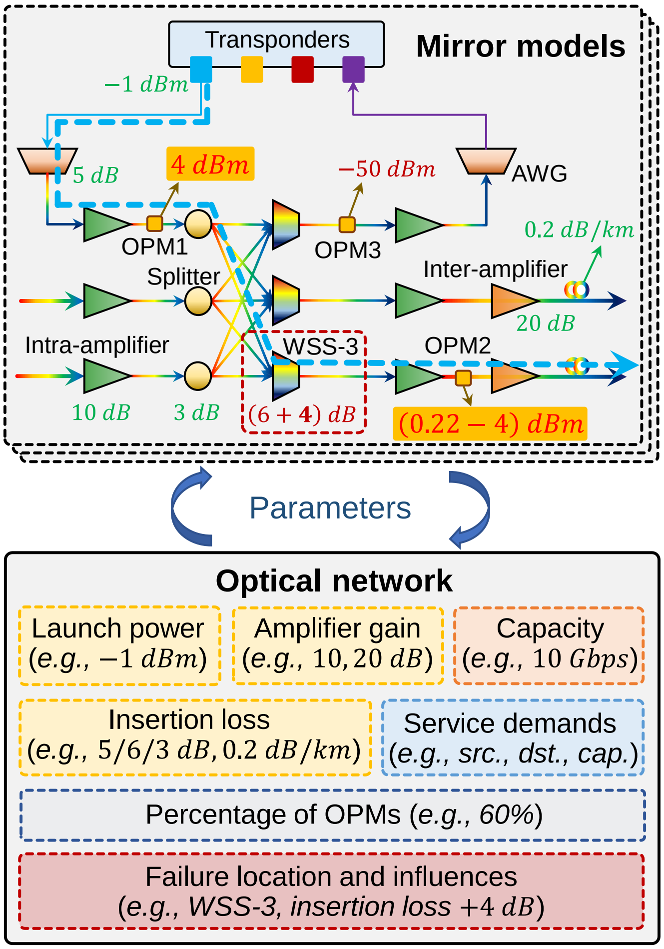

Fig. 2. Example of the mirror models for simulating soft failures based on the collected parameters from optical networks.

line) and OPMs (e.g., in a percentage of 60%) are placed to monitor signal powers. We calculate the monitored values according to routing results. For example, the monitored values of *OPM-1* and *OPM-2* are 4 dBm and 0.22 dBm, respectively[2]. We assume the combination of failure types is attenuation failure, i.e., including fiber spans, splitters, WSSs and AWGs. Thus, a soft failure is generated, e.g., *WSS-3*, and it results in extra attenuation of 4 dB. Thus, *OPM-2* obtains a new value of $(0.22-4)$ dBm. For the OPMs that are not crossed by any service request, like *OPM-3*, their monitoring values are set by default to -50 dBm.

B. Meta Learning for Localizing Soft Failures

After generating multiple training tasks via digital twin, the meta learner can undergo pre-training with the training tasks, and subsequent fine-tuning and testing using the testing tasks. Each testing task is further divided into a support set and a query set to fine-tune and test the meta learner's performance, respectively. In this part, we detail the procedure of meta learning for localizing soft failures with limited real samples.

[2]The initial default launch power of transponder is -1 dBm, and the normal attenuation of AWG and gain of intra-amplifier are 5 dB and 10 dB. Thus, the monitored value of *OPM-1* is $-1-5+10=4$ dBm. In next component, splitter results in the attenuation of 3 dB, and the power value becomes 1 dBm. Besides, splitter will divide power values equally into three parts, and each of them is -3.78 dBm. Afterward, the WSS and intra-node amplifier will bring the attenuation of 6 dB and amplification of 10 dB, respectively. Therefore, the monitored value of *OPM-2* is 0.22 dBm.

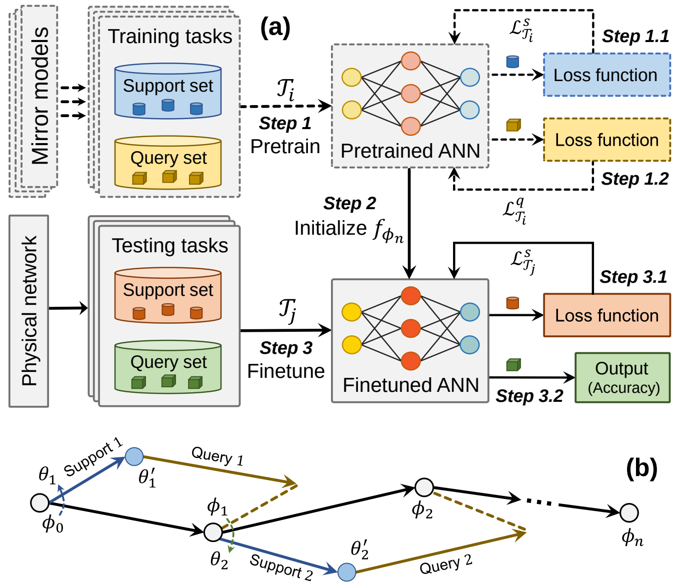

Fig. 3. (a) Pipeline of meta learning for failure localization; (b) Updating procedure of meta learning.

Model Agnostic Meta Learning (MAML) is the most popular meta-learning algorithm since it can be applied to any different models regardless of its architecture or specific learning [37]. In this work, we adopt MAML models and take ANNs as a meta learner, which is denoted by a function f_ϕ with parameters ϕ. Fig. 3(a) shows the pipeline of meta learning for soft-failure localization and it consists of three steps. The first step is to pre-train meta learner based on training tasks. As shown in Fig. 3(a), digital twin is used to build multiple mirror models and then provide training tasks and samples. In pre-training procedure, we replicate the meta learner using function f_{θ_i}, which corresponds to training task $\mathcal{T}_i$. Meta learning adapts to training task $\mathcal{T}_i$ based on the corresponding support set, and updates model parameters θ_i according to its loss function. The following Eq. (1) presents the adaptation procedure of training task $\mathcal{T}_i$:

$$\theta_i^{'} = \theta_i - \alpha \cdot \nabla_{\theta_i} \mathcal{L}^s_{\mathcal{T}_i}(f_{\theta_i}) \qquad \textbf{(1)}$$

where $\theta_i^{'}$ denotes the updated model parameters, α is a learning rate, $\mathcal{L}^s_{\mathcal{T}_i}$ denotes the cross-entropy loss function of the support set in training task $\mathcal{T}_i$. This procedure is detailed in step 1-1, as illustrated in Fig. 3(a).

In next step 1-2, we calculate the gradient for $f_{\theta_i^{'}}$ based on query set, and then update the meta learner $f_{\phi_{i-1}}$ with same gradient:

$$\phi_i = \phi_{i-1} - \beta \cdot \nabla_{\phi_{i-1}} \sum_{\mathcal{T}_i} \mathcal{L}^q_{\mathcal{T}_i}(f_{\theta_i^{'}}) \qquad \textbf{(2)}$$

where ϕ_i represents the updated model parameters of training task $\mathcal{T}_i$, β is a learning rate and $\mathcal{L}^q_{\mathcal{T}_i}$ is the cross-entropy loss of query set in training task $\mathcal{T}_i$.

Fig. 3(b) details the pre-training procedure of meta learning, where ϕ_0 denotes the initial model parameters. During each iteration, e.g., for training task $\mathcal{T}_1$, model parameters ϕ_0 are replicated to θ_1, and then updated to $\theta_1^{'}$ based on support set 1. Afterwards, meta learner ϕ_0 undergoes an update to ϕ_1 using an identical gradient as $\theta_1^{'}$. The procedure described above will be replicated for every training task, and pre-trained model

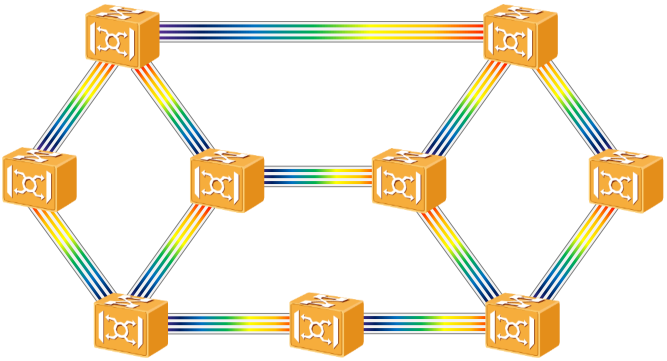

Fig. 4. Experimental testbed topology.

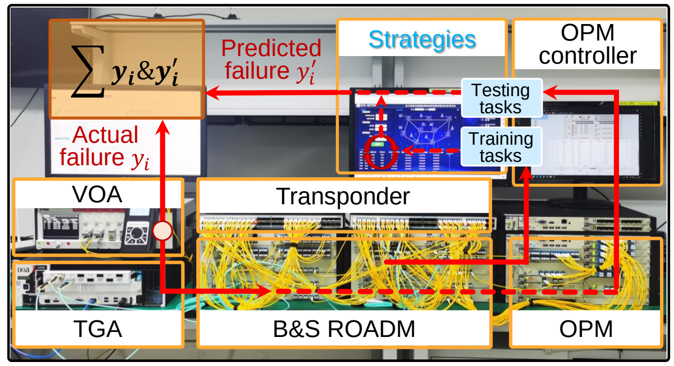

Fig. 5. Experimental testbed and procedure.

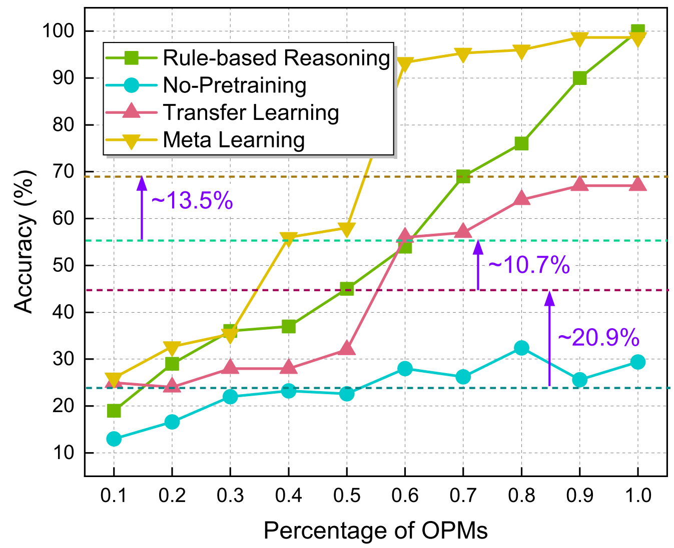

Fig. 6. Testing accuracy vs. percentage of OPMs.

parameters ϕ_n are applied as the initial models in next fine-tuning.

Following pre-training on the training tasks, we initialize the fine-tuned meta learner using the pre-trained model f_{ϕ_n} as depicted in step 2 of Fig. 3(a). In the next step 3, we collect a testing task $\mathcal{T}_j$ from the physical network and use its support set to update meta learner f_{ϕ_n} by Eq. (1). Meanwhile, the query set is responsible for testing the fine-tuned meta learner, and testing results are measured using localizing accuracy of soft failures.

5. EXPERIMENTAL SETUP AND RESULTS

In this section, we present the experimental setup, including the testbed network, experimental procedure and parameters of the proposed solutions. In addition, the experimental results are shown and discussed.

A. Experimental Setup

We evaluate the proposed solution in the 9-node topology shown in Fig. 4. For mirror models, we consider that each node contains three transponders, and for each of them the launch power is $-1\ dBm$. To compensate the attenuation of other components, the gains of inter-/intra-node amplifiers are 15 dB and 20 dB, respectively. The insertion losses of each WSS, splitter and AWG are set as 6 dB, 2 dB and 6 dB, respectively. Fiber spans range from 20 km to 60 km, with 0.2 dB/km attenuation. Besides, we ignore the loss incurred by connectors and intra-node fibers due to their typically minimal impact on the overall attenuation. In our work, these mirror models provide different training tasks, where the number of service requests ranges from 20 to 100 (step by 20), percentage of OPMs varies from 20% to 100% (step by 20%), and combination of failure types consists of 7 distinct elements, i.e., amplification (*Amp.*), attenuation (*Att.*), launch (*Lau.*), *Amp.&Att.*, *Amp.&Lau.*, *Att.&Lau.* and *Amp.&Att.&Lau.*. Therefore, the total number of mirror models is 175 (i.e., $5 \times 5 \times 7$), and each of them corresponds to a training task. Testing tasks are collected from a testbed shown in Fig. 5, where traffic generator and analysis (TGA) equipment is connected with transponders to inject live traffic, variable optical attenuator (VOA) simulates different soft failures, and OPM cards monitor network status (i.e., optical power). In our work, the locations of soft failures are randomly selected and their effects are based on the failure categorization in Table 1.

The proposed meta learner is composed of ANN models with $324 \times 300 \times 216$ neuron architectures, and the learning rates α and β are configured to be 0.001. We consider following three benchmark methods: 1) *Rule-based Reasoning* method iterates through the entire routing results of service requests, and finds the initial occurrence of an abnormal OPM among total abnormal OPMs. The component nearest to the abnormal OPM is the likely failure location. 2) *Transfer Learning* method is pre-trained using the same training-tasks data and then retrains all neural layers based on the testing-tasks data [32]. Subsequently, the retrained model is tested to show localization accuracy. 3) *No-Pretraining* method consists of training only using testing tasks data. In addition, other parameters in all ML-based benchmarks remain consistent with the meta learner, including learning rates and neuron architectures. We pre-train, fine-tune and test all approaches on a personal computer (equipped with AMD Ryzen-7 5800H CPU, and 16-GB RAM). Under this setting, meta learner requires about 5 minutes for pre-training, and 1-2 minutes for fine-tuning. The testing phase of meta learner requires a limited time, i.e., about 1 millisecond for a single sample.

B. Experimental Results and Discussions

In this subsection, we present the numerical results under different settings and discuss the impact of different system parameters on soft-failure localization.

B.1. Testing Accuracy under Different Percentages of OPMs

Fig. 6 reports testing accuracy of the proposed meta-learning approach, compared to the three baselines, under different per-

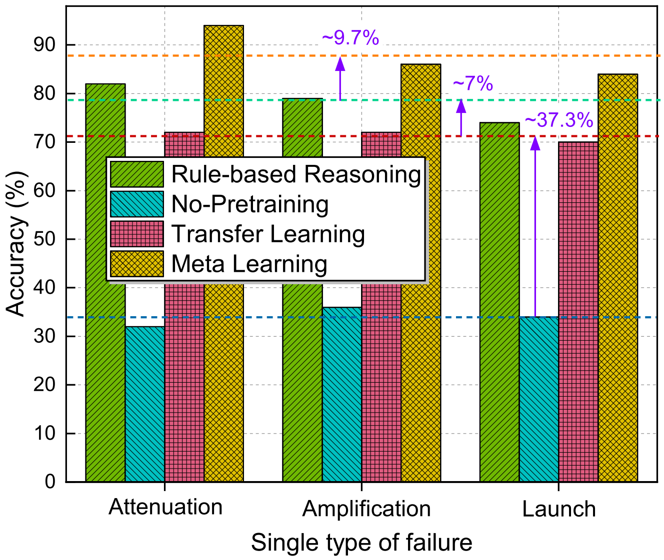

Fig. 7. Testing accuracy under single type of failures.

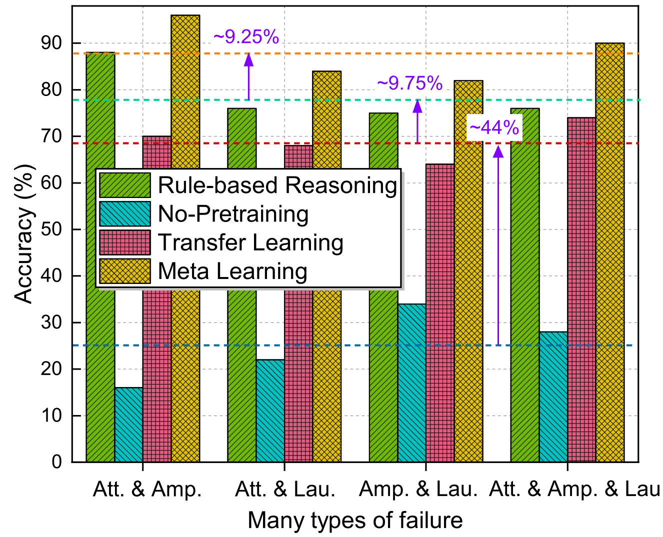

Fig. 8. Testing accuracy under many types of failures.

centages of OPMs. OPMs are deployed as described in Section. 3, each training task includes 50 training samples, the number of service requests is 90, and failure types contain amplification, attenuation and launch failures (*Amp.* & *Att.* & *Lau.*).

Experimental results confirm that the proposed meta learning approach achieves higher localization accuracy for all the values of percentages of OPMs, where the horizontal dotted lines denote average accuracies of different methods. More precisely, meta learning improves accuracy of 13.5%, 24.2% and 45.1% on average compared to rule-based reasoning, transfer learning and no-pretraining, respectively. Note that rule-based reasoning method achieves higher accuracy than other benchmarks. The reason is that all ML-based methods are fine-tuned (or trained) only using limited real samples. In addition, we can observe that adding OPMs improves testing accuracy in localizing soft failures, in all the four methods, as more OPMs enable more precise monitoring. However, this also leads to an increase in CapEx for network operators. Another significant trend emerging from these results is the rapid increase in localization accuracy as the percentage of OPMs shifts from 50% to 60%. This trend suggests that deploying OPMs at levels exceeding 50% is a favorable choice for monitoring network status, but further investigation is needed to determine the optimal deployment of OPMs.

B.2. Testing Accuracy under Different Combinations of Failure Types

We now analyze the testing accuracy across various combinations of failure types, while maintaining a constant number of training samples as detailed in Section 5.B.1. In this scenario, there are 90 service requests and with a percentage of OPMs equal to 80%.

Fig. 7 shows the testing results under a single failure type, i.e., only attenuation failure, amplification failure or launch failures. The results indicate that meta learning improves accuracy of 9.7%, 16.7% and 54% on average compared to rule-based reasoning, transfer learning and no-pretraining methods, respectively. The failure type does not greatly affect localization accuracy, as different soft failures all result in abnormal monitoring values. Meanwhile, Fig. 8 shows the localization accuracy under various combinations of multiple failure types. There are four failure combinations: 1) attenuation failure and amplification

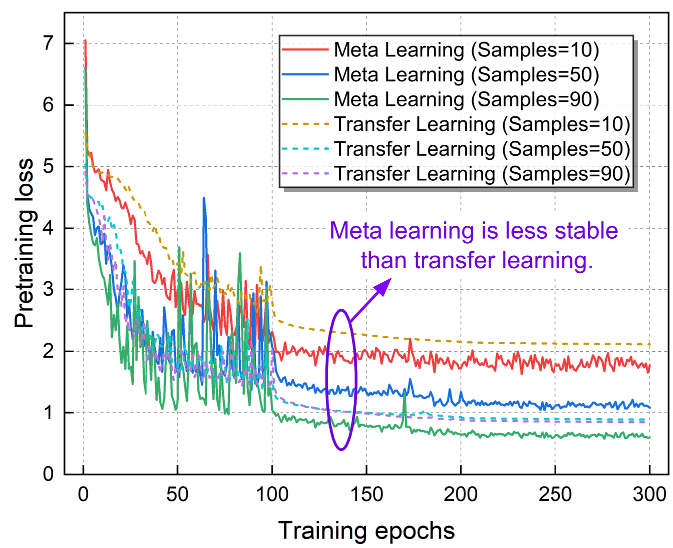

Fig. 9. Pre-training loss values under different number of training epochs.

failure, i.e., Att.&Amp., 2) attenuation failure and launch failure, i.e., Att.&Lau., 3) amplification failure and launch failure, i.e., Amp.&Lau., and 4) attenuation failure, amplification failure and launch failure, i.e., Att.&Amp.&Lau. The results indicate that, in comparison to a single failure type, meta learning obtains similar localizing accuracy, while the benchmarks experience a decrease in localizing accuracy. For example, localization accuracy of no-pretraining decreases 9% when comparing single failure type to scenarios involving multiple failure types. The above results demonstrate that the proposed meta learning has a strong adaptability for different soft failures.

B.3. Pre-training Loss under Different Training Epochs

In this subsection, we visualize the pre-training procedure and illustrate the impact of different sample sizes within each training task on experimental results. Fig. 9 compares the pre-training loss of transfer learning vs. the proposed meta learning approach, for varying numbers of training epochs. Each training epoch comprises 175 distinct training tasks, as detailed in Section

5.A.

The trend indicates a rapid decrease in pre-training loss values, followed by convergence to stable values after surpassing 200 training epochs. Furthermore, the pre-training loss values are plotted for increasing sample sizes (from 10 to 90) within each training task. It can be observed that a higher number of samples contributes to the decrease of the pre-training loss, since a larger sample size enables the ML models to capture more features of soft failures. In addition, meta learning is less stable than transfer learning. The reason is that transfer learning primarily aims to minimize loss values across all training tasks, whereas meta learning prioritizes enhancing adaptability and swift learning capabilities for novel tasks.

6. CONCLUSION

In this study, we investigated the problem of soft-failure localization, within inter-/intra-node components of ROADM-based optical networks, in case of limited availability of training samples. We categorized some potential soft failures between inter- and intra-node components and devised a failure categorization to facilitate our investigation. Meanwhile, a digital-twin-assisted meta-learning framework is proposed to achieve soft-failure localization. This framework leverages digital twins to construct mirror models and provide multiple training tasks. Subsequently, meta learning is trained to effectively localize soft failures. The proposed framework is evaluated in an 9-node testbed network, and extensive experimental results show that the proposed meta learning improves localization accuracy by approximately 15%, 33% and 54% on average compared to rule-based reasoning, transfer learning and no-pretraining methods, respectively. The proposed approach can accurately locate soft failures with limited samples.

Considering soft failures localization in ROADM-based optical networks, there are several crucial challenges that require to be further investigated. For instance, when the telemetry interval is large, multiple components may fail simultaneously, especially as the degree of ROADMs increases significantly. On the other hand, soft-failure localization depends on extensive network telemetry, requiring intricate design for network orchestration and management. In the future, we plan to study multi-soft-failure localization approaches and design the detailed control procedure.

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