Crosstalk Tracing in Weakly-Coupled Short-Reach Mode-Division Multiplexing Optical Networks with Deep Learning

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Abstract: We propose a crosstalk tracing method using deep neural networks for weakly-coupled MDM optical networks. Results show that over 95% tracing accuracy is achieved and the impact of time consistency in data collection is revealed.
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1. Introduction

In recent years, the traffic of short-reach networks such as intra-datacenter networks (intra-DCNs) and high performance computing (HPC) systems has sustained exponential growth [1, 2]. To enlarge transmission capacity, researchers have proposed the concept of weakly-coupled mode-division multiplexing (MDM) transmission [3-5], in which signals on each mode are transmitted as independent channel, and the accumulated crosstalk along the lightpath needs to be optimized below a threshold, otherwise the bit-error ratio (BER) may be unacceptable [6, 7].

However, lightpath crosstalk evaluation implicates the assessment of the crosstalk effect on every consisting links, which involves complex and time-consuming computations especially for the network scenarios due to the high-order crosstalk effects and the ever-changing link occupation states [7]. Moreover, it is more complicated to trace the crosstalk (find out every interfering channel whose crosstalk value is beyond the threshold) to achieve crosstalk optimization through lightpath reconfiguration. In literature [6], researchers have proposed a crosstalk monitoring method which separates the signal and crosstalk in frequency domain using pilot tones for point-to-point multicore fiber (MCF) transmission systems. However, this method is difficult to be extended to network scenarios due to the requirement of huge amount pilot tones which will occupy a large number of wavelength resources. Literature [7] has proposed an in-service network crosstalk monitoring and tracing method for complex network scenarios, which separates the signal and crosstalk in time domain using fine-grained time slices, but it still consumes extra link resources to establish monitoring channels.

To achieve in-service crosstalk tracing without consuming extra resources under complex network scenarios, machine learning (ML) is a promising method, due to its capability of mimicking a complex system model faster with less information [8-10]. In previous works [8-10], complex optical network problems such as quality of transmission (QoT) estimation, optical amplifiers control and optical performance monitoring have been solved through ML methods. However, ML-based crosstalk tracing in MDM optical networks is still at blank.

In this paper, we propose a novel deep neural network (DNN)-based in-service crosstalk tracing method for short-reach weakly-coupled MDM optical networks. In this method, DNNs are trained to trace interfering channels which create crosstalk beyond a threshold in the channels being monitored, requiring no extra network resources but only the data of optical channels powers and the switches states. We validate the feasibility of the proposed method through a prototype experiment and achieve 100% tracing accuracy. Moreover, we conduct a nine-switch-node MDM intra-DCN simulation and the results show that over 95% tracing accuracy can be achieved. The results also reveal the impact of time consistency in data collection on tracing accuracy.

2. DNN-based crosstalk tracing method

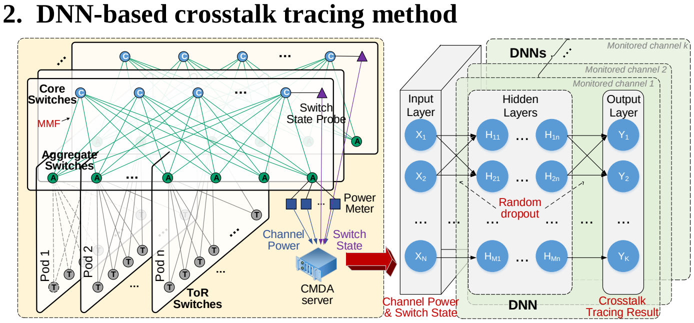
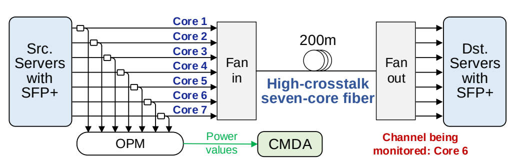


Fig. 1. Concept of DNN-based in-service crosstalk tracing



DNN data sets acquired by the method in [7]

Data Set	Sample ID	DNN Input							DNN Output (crosstalk power: mW)						
Training	1	0	1	1	0	0	1	1	0	0(0.0004)	0(0.0002)	0	0	1(0.96)	1(0.03)
	2	0	0	0	1	0	1	0	0	0	0	0(0.001)	0	1(0.96)	0
	…	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	80	1	0	1	1	1	1	1	1(0.10)	0	0(0.0002)	0(0.001)	1(0.12)	1(0.96)	1(0.03)
Testing	81	0	0	0	0	0	0	1	0	0	0	0	0	0	1(0.03)
	…	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	100	0	0	1	1	0	0	0	0	0	0(0.0002)	0(0.001)	0	0	0

Fig. 2 Prototype experiment and data sets

We take an MDM-enabled intra-DCN as an example to explain our DNN-based crosstalk tracing method as shown in Fig. 1. In our method, the data source needed for DNN inputs is the powers of certain mode channels and the states of the optical switches which can be measured by power meters and switch state probes, respectively. DNNs are running on a crosstalk monitoring and data analytics (CMDA) server to trace the interfering channels whose crosstalk value is beyond a pre-set threshold (each DNN for one monitored channel). Each element in the output layers of the DNNs is binary, indicating whether an interfering optical channel creates crosstalk beyond the threshold in the channel being monitored. The random dropout method [11] is used to prevent DNNs from overfitting.

3. Prototype experiment and results

A prototype point-to-point experiment is carried out to evaluate the performance of the proposed DNN-based crosstalk tracing method. The experimental setup is shown in Fig. 2. A 200-m special tapered high-crosstalk seven-core fiber is applied to mimic weakly-coupled MDM transmission. An optical power meter (OPM) is deployed to measure the powers of core channels and send the power values to the CMDA server. DNNs are running on the CMDA server to achieve crosstalk tracing.

The time slice crosstalk monitoring method in literature [7] is used to acquire the data sets for DNN training and testing. Core 6 is selected as the monitored channel. Both of the DNN input layer and output layer have 7 elements which are corresponding to the 7 core channels. The table in Fig. 2 shows the DNN inputs and outputs when the crosstalk tracing threshold is set to -20 dB. Three hidden layers and two random dropout layers are alternatively arranged. The dropout probability is set to 50%. After training the DNN, the tracing accuracy of the testing data set reaches 100%. The result validates the feasibility of the proposed method in point-to-point weakly-coupled MDM scenario.

4. Simulation and performance analysis in network scenarios

To evaluate our method in complex network scenarios with high-order crosstalk effects, we conduct a simulation in a fat-tree intra-DCN as shown in Fig. 3. The network consists of 3 core switches (C1~C3), 6 aggregate switches (A1~A6) and 18 pairs of bidirectional 500-m MMFs. Four spatial channels (modes) are transmitted over each MMF with the crosstalk values set according to the experimental results in literature [12]. Each aggregate switch connects to every core switch with 12 mode ports (e.g. P1~P12 for A1). The LP_{01} mode channel of the aggregate switch A1 is selected as the channel being monitored. The crosstalk tracing threshold is set to -20 dB. The original data set which contains 20000 samples is acquired through network simulation. The training, cross-validation and testing data sets take 70%, 10% and 20% of the original data set, respectively.

The input layer of the DNN has 504 elements in total, 72 elements for the modal channel powers and 432 elements for core switches states. Four hidden layers and three random dropout layers are alternatively arranged. The dropout probability is set to 50%. The output layer has 72 binary elements, indicating whether the interfering modal channels creates crosstalk beyond the pre-set threshold.

After training the DNN, the tracing accuracies of both training and cross-validation data sets reach 100%. The average tracing accuracy of the testing data set is 95.6%. Fig. 4 shows the tracing accuracies for all the 20 modal channels which may create crosstalk in the channel being monitored (channels passing through core switch C1). It can be seen that the accuracies for 95% channels exceeds 90% and the lowest is 88.9% (Channel 26).

We also conduct a simulation to evaluate the impact of time consistence in data collection. The average traffic arrival interval is set to 0.01s while the time error range is set varied from 0 to 0.5s. From the result shown in Fig. 5, we find out that the average tracing accuracy degrade from 95.6% to 58.1% when the time error range enlarges to 0.5s. In order to maintain over 90% tracing accuracy, the time inconsistence in data collection should be at least an order of magnitude smaller than the average traffic arrival interval.

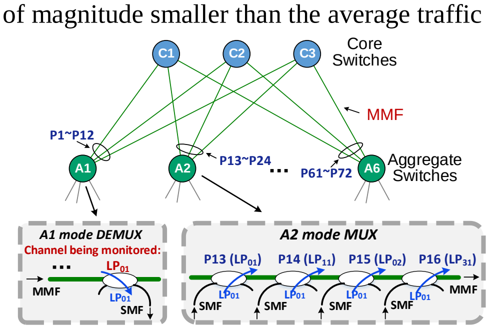


Fig. 3 Simulation setup

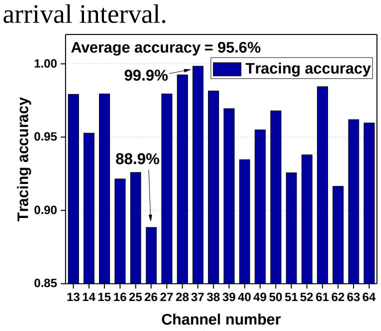


Fig. 4 Channel-specific tracing accuracy

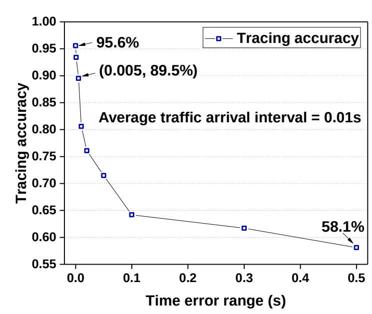


Fig. 5 Tracing accuracy vs. time error

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