Experimental Demonstration of Automated ML Service Provisioning for VNT Configuration in SDM Networks

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Abstract: This paper demonstrates automated ML service provisioning for virtual network topology (VNT) configuration over a 7-core fiber SDM testbed. Results show below 3-second VNT configuration time and provisioning of QoT estimators with $>90\%$ accuracy using <100 samples.

1. Introduction

As the capacity of optical fibers approaches the Shannon limit, space division multiplexing (SDM) has emerged as an attractive solution for meeting the ever-increasing traffic demand [1]. SDM networks achieve significant capacity gains by parallelizing the transmission and switching of signals across multiple spatial dimensions (fiber cores or spatial modes of light). In the meantime, network virtualization technologies bring unprecedented flexibility in service provisioning by configuration of virtual network topologies (VNTs) or slices with diversified quality-of-service assurances over physical substrates. It is envisioned that the combination of network virtualization with SDM will facilitate fully exploiting the multi-dimensional resources of SDM networks [2].

Conventionally, substrate operators provide tenants abstracted views of their VNTs, which limits the manageability and therefore hinders the effective utilization of the allocated resources. Such challenges can potentially be met by machine learning (ML) applications owing to their capability of learning complex rules from data without explicit physical models. Indeed, recent studies have reported successful applications of ML in optical networks such as quality-of-transmission (QoT) estimation, resource allocation and fault management [3]. While ML actuates automated and cognitive optical networking, provisioning of ML models often relies on laborious model configuring and tuning by network experts, which can burden the dynamic provisioning of VNTs. The ML-as-a-service framework [4] initiates the attempt to automate the provisioning of ML services, but little effort has been made in optimizing ML models for VNTs under limited network visibility.

In this work, we demonstrate automated ML service provisioning for VNT configuration over an SDM testbed composed of field-deployed 7-core fibers. We first present a software-defined networking (SDN) control plane architecture and a multi-granularity SDM node structure for VNT configuration. Then, the model-agnostic-meta-learning (MAML) algorithm is applied for automated optimization (model selection and training) and provisioning of QoT estimation tools for VNTs. Experimental results show VNT configuration in below 3 seconds, with the provisioned QoT estimator achieving over 90% accuracy using less than 100 training samples.

2. Principle

Network architecture: Fig. 1(a) depicts the architecture of an SDN-enabled multi-core fiber (MCF) SDM network. The SDM nodes, whose structures are shown in Fig. 1(b), perform multi-granularity switching in core and spectrum dimensions. Specifically, an SDM node is composed by a spatial cross-connect (SXC) that either directs an entire core to the desired output port or distributes the wavelength channels in it individually using a loop-back structure and a wavelength selective switch (WSS). Fan-in and fan-out devices are used for interfacing MCFs with the SXC. Each SDM node is equipped with the optical performance monitoring (OPM) functionality that can measure multiple parameters including power, noise level, etc. An SDN agent is deployed locally at each node to stream OPM data to the SDM network controller. To support creation and management of VNTs over the SDM substrate, a network virtualization hypervisor (NVH) is placed on the top hierarchy. The NVH communicates with the SDM controller to receive substrate network models, computes the node and link mapping for VNTs, and provisions cognitive functionalities (ML services) to the VNT controllers.

VNT configuration workflow: Fig. 1(c) shows the proposed workflow for VNT configuration. First, the NVH receives a tenant request for configuration of a VNT and ML functionalities conveyed by the source and destination

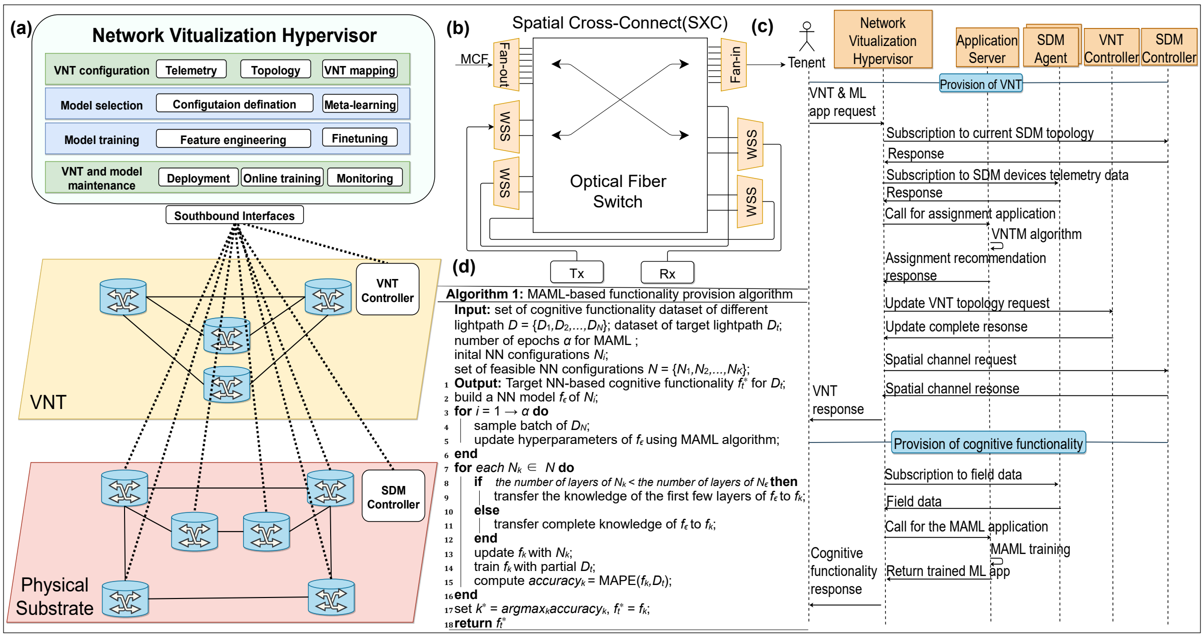

Fig. 1: (a) SDN-based SDM network architecture; (b) multi-granularity SDM node structure; (c) workflow of VNT configuration and ML service provisioning; and (d) MAML algorithm.

nodes, QoT and bandwidth requirements, etc. It acquires the current substrate SDM topology from the SDM controller and then invokes the VNT mapping (VNTM) algorithm (deployed externally in an application server) to compute the node and link mapping as well as the spatial/spectral channel allocation (based on the QoT and bandwidth requirements) for the requested VNT. Afterward, the NVH informs the SDM controller to complete the VNT configuration by isolating and aligning the reserved resources.

Cognitive functionality provisioning: After configuration of the VNT, the NVH calls the cognitive functionality provisioning module to instantiate the requested ML services for the tenant. In this work, we perform a case study on the provisioning of QoT estimators. We adopt the MAML algorithm shown in Fig. 1(d), which is a model-agnostic meta-learning approach successfully applied to a wide range of learning tasks such as classification, regression, and reinforcement learning [5]. The basic idea of MAML is to derive performant model initialization through acquisition of meta-learned knowledge. More specifically, we first train an initial model f_ε using MAML's gradient descent method, which utilizes a gradient by gradient strategy and involves two rounds of gradient update processes. During each training epoch, we initially calculate the gradient of the model and update the parameters multiple times for each task in the batch, completing the first round of gradient updates. Subsequently, based on the parameters obtained from the first round, the second round of gradient updates is performed using the gradient by gradient strategy, directly applied to the original model. In essence, the purpose of the first round is to prepare for the second round, which is the actual process focused on updating the model parameters. Next, the algorithm iterates through a set of feasible model configurations, i.e., neural networks (NNs) of different numbers of layers. For each configuration, the first $\min\{N_\varepsilon, N_k\}$ layers of f_ε are migrated to f_k. Next, f_k is trained using a small amount of data of D_t, and the accuracy is computed represented by mean absolute percentage error (MAPE). Subsequently, the algorithm returns the f_t^* configured by N_k with the highest accuracy. Finally, f_t^* is sent to the tenant through the NVH. Note that, the provisioned QoT estimator is trained for substrate lightpaths and therefore should be encapsulated by a VNT-to-substrate mapper transparent to the tenant.

3. Experimental results

We conducted automated VNT configuration experiments over a four-node SDM testbed shown by Fig. 2(a). Each SXC node was implemented by an optical switch sliced from a large-port-count Polatis matrix switch. The testbed consists of two 16.5-km 7-core fibers deployed in the field [6] and two standard single-mode fibers. We set up optical connections with transponders operating at 16-32 GBaud and applying the QPSK or 16QAM modulation. We set up an SDN control plane system based on the ONOS platform with the NVH deployed externally in a stand-alone machine. The southbound and northbound interfaces were implemented by the NETCONF protocol and secured TCP connections, respectively, for the communications between the controller, the SXCs and the NVH.

Fig. 2(c) shows the control plane signaling in establishing a three-node VNT. First, the tenant initiated a 3-node

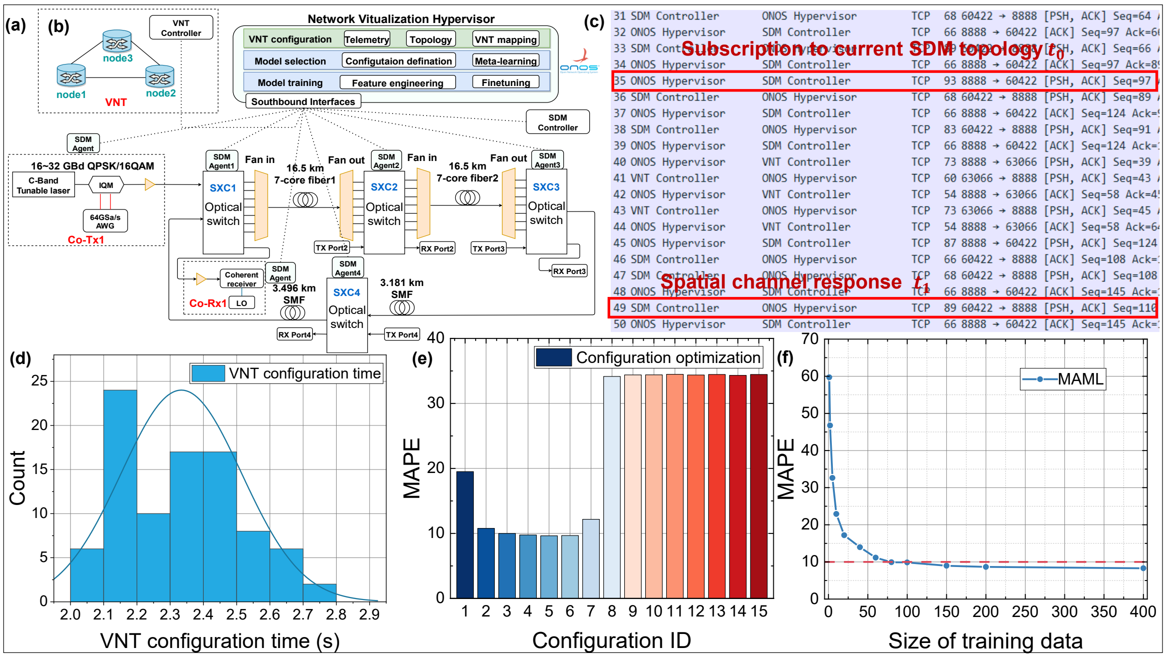

Fig. 2: (a) Experimental setup; (b) VNT request by the tenant; (c) control plane signaling for VNT configuration; (d) VNT configuration time histogram; (e) accuracy of different NN configurations; and (f) performance of the provisioned QoT estimator under different sizes of training data set.

VNT request as shown by Fig. 2(b). The target baud rate, modulation format and QoT (BER) bound are 32 GBaud, 16-QAM, and 1.2e-3, respectively. Next, the NVH subscribed to the current SDM topology at t_0. Based on the current resource utilization and the QoT target by the request, the NVH decided to map the VNT to SXCs 1, 3 and 4, and allocated SXC1-SXC2-SXC3 (core #2, core #4), SXC3-SXC4, and SXC4-SXC1 as the virtual links. The NVH then instructed the SDM controller to configure the SXCs accordingly and instantiated a VNT controller for the tenant. A spatial channel response was received at t_1, indicating the successful configuration of the VNT. The whole process took 2.1 seconds. Fig. 2(d) presents the distribution of VNT configuration time over 90 independent experiments. The VNT configuration time averages 2.3 seconds and is upper bounded by 2.8 seconds.

After successful configuration of the VNT, the NVH executed Algorithm 1 to provision the tenant a QoT estimator capable of modeling the transmission properties of the virtual links. The algorithm used $2,322$ samples in total, $1,611$ out of which formed a generic data set while the rest were collected specifically for the VNT. In order to collect the data, we set up five lightpaths. We set up the transmitter at SXC1 and set up the receiver at SXC1, SXC3 and SXC4, respectively. The fiber cores traversed of 7-core fiber1 were cores #1, #2, #4 and #7. The fiber cores of 7-core fiber2 traversed were cores #3, #4 and #6. The modulation formats used were QPSK and 16QAM. The baud rates ranged from 16 to 32 GBaud. The current of the EDFAs traversed ranged from 40 to 76 mA. We provided 15 feasible NN configurations with the number of layers ranging from 1 to 15. Fig. 2(e) shows the MAPE of the 15 configurations. The algorithm selected configuration 5 which has the lowest MAPE as the target configuration. The performance of the provisioned QoT estimator under different sizes of training set is illustrated in Fig. 2(f). With 80 training samples, it could achieve $>90\%$ prediction accuracy on the testing set.

4. Summary

Aided by an MAML approach, this paper demonstrated automated VNT configuration with cognitive functionality provisioning over a field-deployed SDM testbed using 7-core fibers.

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