Meta-learning-aided QoT estimator provisioning for dynamic VNT configuration in optical networks

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Machine learning (ML) based quality-of-transmission (QoT) estimation tools will be desirable for operating virtual network topologies (VNTs) that disclose only abstracted views of connectivity and resource availability to tenants. Conventional ML-based solutions rely on laborious human effort on model selection, parameter tuning and so forth, which can cause prolonged model building time. This paper exploits the learning-to-learn nature by meta learning to pursue automated provisioning of QoT estimators for dynamic VNT configuration in optical networks. In particular, we first propose a graph neural network (GNN) design for network-wide QoT estimation. The proposed design learns global VNT representations by disseminating and merging features of virtual nodes (conveying transmitter-side configurations) and links (characterizing physical line systems) according to the routing schemes used. Consequently, the GNN is able to predict the QoT for all the end-to-end connections in a VNT concurrently. A distributed collaborative learning method is also applied for preserving data confidentiality. We train a meta GNN with meta learning to acquire knowledge generalizable across tasks and realize automated QoT estimator provisioning by fine tuning the meta model with a few new samples for each incoming VNT request. Simulation results using data from two realistic topologies show our proposal can generalize QoT estimation for VNTs of arbitrary structures and improves the estimation accuracy by up to 18.7% **when compared with the baseline.**

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1. INTRODUCTION

Infrastructure-as-a-Service (IaaS) [1] promotes customized and quality-of-service-assured network service provisioning by configuring virtual network topologies (VNTs), also known as network slices, with isolated bandwidth and computing resources. One of the most relevant problems on IaaS is VNT embedding [2], which aims at optimizing the mapping of virtual nodes and links to the physical substrates. While extensive studies have been reported in this aspect [2–4], how to realize effective management of VNTs (performance assessment, capacity maximization, etc.) remains a nontrivial problem because substrate network operators typically disclose only limited information to tenants (VNT managers) for privacy considerations. This is especially true under the regime of optical spectrum as a service (OSaaS) driven by the trend of optical network disaggregation, where operators and tenants manage optical line systems and transponders separately [5, 6]. Consequently, tenants will urge specific network control and management services that can interface with both entities (in compliance with data privacy constraints) for deriving correct spectrum allocation schemes and transponder configurations, for instance, relying on a quality-of-transmission (QoT) estimator for margin optimization.

Over the past years, machine learning (ML) has emerged as a focal point for the research community targeting optical network automation and intellectualization (e.g., self-driving optical networks [7]). ML allows for learning complex rules directly from data without explicit programming or understanding of the inherent problem structures. Such a data-driven nature of ML makes it especially appealing for tackling VNT management tasks. Previous works have demonstrated encouraging results from ML applications in optical networks [8, 9], such as QoT estimation [10], fault management [11], routing and spectrum assignment [12], and VNT embedding [13].

Despite the great stride in ML algorithm and application designs, actuating ML service provisioning for VNTs encounters a major obstacle of prolonged ML model building time. In particular, an ML service provisioning pipeline [14] involves multiple stages such as data collection, model selection, training and operation, many of which rely on laborious human interventions. Therefore, accelerating ML service establishment becomes highly desired for dynamic VNT configuration, where VNTs need to be configured on demand and timely. Existing works pursue this goal mainly by leveraging transfer learning approaches to ease the training procedures [15, 16]. More recently, a Machine-Learning-as-a-Service (MLaaS) framework has been proposed for automating ML service provisioning in optical networks [14]. Nevertheless, ML service automation designs for dynamic VNT configuration under data confidentiality constraints remain under explored.

This paper extends our previous work in [17] and presents a meta-learning-aided automated QoT estimator provisioning design for dynamic VNT configuration in optical networks. Our contributions over the previous publication include: (1) proposing a graph neural network-based network-wide QoT estimator design for VNTs, which can predict the QoT for all the end-to-end connections in a VNT concurrently and generalize VNTs of arbitrary topologies; (2) introducing a distributed collaborative learning method for data privacy conservation in QoT estimator provisioning; and (3) presenting extensive results by evaluating the proposed design under various parameter configurations and application scenarios.

The rest of the paper is organized as follows. In Section 2, we overview the recent progresses on ML-based QoT estimation and VNT embedding. Section 3 presents an architecture supporting ML service automation for dynamic VNT configuration. In Section 4, we elaborate on the principle of the proposed design. Section 5 provides the simulation results and related discussions. Finally, we conclude the paper with Section 6.

2. RELATED WORKS

A. QoT Estimation

QoT estimation is an essential task in optical networks. Traditional QoT estimation methods rely on mathematical modeling of the transmission process in the physical layer. One of such methods is the split-step Fourier method (SSFM) [18], which can accurately obtain the QoT results of lightpaths through numerical simulation. However, its high computational complexity makes it unsuitable for providing timely results in real-time systems. Another method is the Gaussian noise (GN) model [19], which simplifies fiber nonlinear effects to reduce the complexity of QoT estimation. The limitation of the GN model lies in its conservative approximation of nonlinear impairment by considering full spectrum load conditions and the inaccuracies in scenarios where the underlying assumption (i.e., the transmitted signal is Gaussian noise) is violated. Consequently, operators need to allocate carefully designed margins to compensate for the inaccurate predictions.

Lately, applying ML for QoT estimation has become the main stream. Previous studies have employed various ML models, such as random forest (RF), support vector machine (SVM), and deep neural networks (DNNs) [20]. In [21], the authors employed the K-nearest neighbors (KNN) and RF algorithms for QoT classification tasks, achieving classification accuracies of 91% and 96%, respectively. In [22], the authors used artificial neural networks (ANNs) for QoT prediction, achieving an accuracy of 95% on the testing set. In [23], a comparative experiment was conducted using SVM and ANN under different conditions, with both methods achieving accuracies up to 99%. Because data for optical network applications are often scarce, it is crucial to consider how to achieve high-performance models in data-constrained conditions. The authors of [24] applied transfer learning (TL), which reuses the models trained on existing networks to reduce the uncertainty of generalized signal-to-noise ratio (GSNR) estimation for a different network. The simulation results demonstrated that the average margin could be reduced from 0.76 dB to 0.58 dB. In [15], an evolutionary transfer learning approach was proposed for predicting the QoT of cross-domain lightpaths. Comparative studies under various conditions showed that this method could reduce the required training samples by up to 13$\times$ while maintaining an accuracy of over 95%. In [25], Meng et al. proposed a monitoring-on-demand strategy that leverages Bayesian optimization to determine the channels to be monitored at intermediate nodes. The experimental results revealed that the proposed strategy could reduce the required monitoring data by up to 91% compared with pure Gaussian process learning. Similarly, the authors of [26] generated a model based on Gaussian processes and used active learning to dynamically select training samples to reduce prediction uncertainty. They showed that the number of training samples required could be reduced by 5% to 75%. In [16], a sample selection method was proposed, utilizing a filtering algorithm in the pre-training stage to identify samples better suited for fine-tuning, and thereby, reducing the number of pre-training samples needed. The results showed that this method could reduce the required pre-training samples by up to 28.5% while surpassing the prediction performance of traditional TL approaches. In [27], the authors proposed an invariant convolutional neural network along with an evolution-update framework. This framework permits inputs that consist of varying numbers of transmission parameters, enabling its deployment under different link configurations. This approach also enhances the model's scalability and reduces the number of required training samples to a certain extent.

Other works address the QoT estimation problem in different network scenarios. In [28], the authors studied QoT estimation in the dynamic network slicing context. They proposed both centralized and decentralized frameworks, as well as a dynamic multi-slice QoT-aware framework, to meet the varying QoT requirements of different slices. The results showed that the decentralized QoT prediction model outperformed the centralized one. The authors of [5] proposed a channel-probing toolkit consisting of symbol rate variable extended channel probing, frequency sweep, and operation regime detection for OSaaS performance assessment. GSNR estimation accuracies of 0.05 and 0.32 dB were achieved for wide-band and narrow-band spectrum services, respectively. Later on, the same authors investigated concatenated link performance estimation through channel probing in a production OSaaS environment [29] and achieved an estimation accuracy of $\pm$1.4 dB for wide-band services. In [30], a knowledge-defined networking framework based on distributed collaborative learning was proposed for multi-domain networks. By deploying distributed ML models, this approach could learn the knowledge of different domains while securing domain privacy. The results indicated that this framework could achieve performance close to that of baseline models assuming full domain visibility. Recently, Yang et al. demonstrated a cascaded traffic-aware ANN-based link-penalty model that can perform concurrent QoT prediction for multiple channels with a precision of $\pm$0.16 dB [31]. In [32], the authors proposed a deep convolutional neural network for network-wide QoT estimation. However, this method subjects to scalability and generalization issues as the employed neural network scales up with the size of network topology and fails to mine the topological correlations among lightpaths.

B. VNT Embedding

In [2], the authors investigated the problem of virtual optical network embedding (VONE) over flexible-grid elastic optical networks under both transparent and opaque configurations. They designed a heuristic algorithm based on a layered-auxiliary-graph which can significantly reduce request blocking probability compared with the baselines. In [33], Gong et al. aimed at solving the location-constrained virtual network embedding (LC-VNE) problem. An LC-VNE algorithm based on a compatibility graph was proposed to achieve integrated node and link mapping. In [34], the authors focused on the VNT reconfiguration problem in hybrid optical/electrical datacenter networks. Experimental results showed that their method outperforms existing methods and achieves near-optimal solutions. In [4], leveraging the parallel transmission characteristics of optical fibers, the authors focused on reducing the complexity of network topology to achieve efficient VNT embedding. They formulated a mathematical model and proposed a location prioritized VNT embedding algorithm based on node proximity sensing and path comprehensive evaluation. The results showed that their algorithm improves the request acceptance rate by 13% compared with the existing algorithms. Recently, ML has also been applied for VNT embedding [13, 35]. In particular, the authors of [13] proposed to divide a VNT into subgraphs and use a deep reinforcement learning (DRL) method to find the most suitable substrate resources for tenants. The experiments demonstrated that their framework achieves reduced computation time and comparable blocking performance.

Despite the advances in QoT estimation and VNT embedding, provisioning of ML-based QoT estimators for VNTs has rarely been addressed. This entails further studies for meeting the challenges of automating the provisioning pipeline and sustaining desirable model generalization ability and scalability while preserving data confidentiality.

3. NETWORK ARCHITECTURE

Fig. 1 depicts an envisioned meta-learning-aided network architecture supporting ML service automation for dynamic VNT configuration. The architecture employs a three-hierarchy network control and management paradigm, where a substrate network manager and a VNT manager configure the physical and virtual resources [using software-defined networking (SDN) controllers] respectively, while a VNT orchestrator (VNT-O) sits in the top hierarchy to coordinate the operations of the two entities. A VNT request can be modeled as composed of a set of virtual nodes and links with certain capacity requirements, and the desired ML services for QoT estimation, routing, modulation and spectrum assignment (RMSA), fault management, and so on. Upon receiving such a request, VNT-O first makes the substrate manager embed the requested virtual nodes and links onto proper physical nodes and links by configurations of the related optical switches (*step 1*). For instance, a virtual link with a capacity of two wavelengths can be mapped onto a multi-hop path in the substrate allowing λ_1 and λ_2 to propagate end to end. VNT-O then instantiates an SDN controller for the VNT manager (*step 2*), providing interfaces that allow the VNT manager to manipulate the allocated resources according to an abstracted view. Afterward, VNT-O applies a meta learning framework for automated ML service provisioning. In the offline training phase (*step 3*), VNT-O retrieves data related to the requested ML services from its database and performs meta training to obtain a set of meta models. The principle of

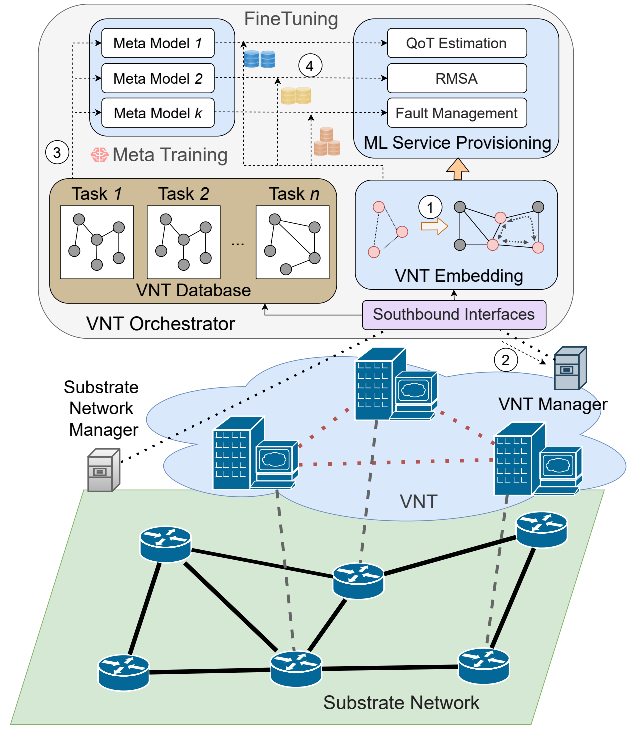

Fig. 1. Meta-learning-aided network architecture for ML service automation.

meta training will be detailed in Section 4.C. These meta models encapsulate knowledge generalizable across different tasks (ML services for different VNT configurations) and serve as templates for creation of new ML models. In the online provisioning phase (*step 4*), VNT-O coordinates the substrate and VNT managers to collect a few additional samples for each ML service, initializes an ML model with the corresponding meta model, and performs fine tuning with the new data. Note that, the substrate and VNT managers may report encrypted data due to privacy considerations, and therefore, the offline training and provisioning phases also involve distributed collaborative learning procedures for joint optimization of the ML models and the encryptors (see Section 4.B). Finally, the architecture can realize agile ML service provisioning for dynamic VNT configurations.

4. QOT ESTIMATION SERVICE AUTOMATION

In this section, we delineate the provisioning of network-wide QoT estimators for dynamic VNT configuration as a case study on meta-learning-aided ML service automation.

A. GNN-based Network-wide QoT Estimation

VNTs feature highly diversified topological characteristics in terms of the numbers of virtual nodes and links, connectivity, and notably, the sets of substrate nodes and links/paths VNTs are mapped onto. Provisioning VNTs with end-to-end QoT estimators can either be costly when training a separate model for each connection or face challenges of generalizing diverse lightpath configurations when training a universal model. In this work, we opt for building network-wide QoT estimators with a GNN-based design which has been demonstrated to be a powerful tool in learning generalizable graph representations from topological data [36]. Algorithm 1 outlines the procedures of the proposed GNN design.

1) Graph data construction. We construct a graph-structured data sample for each VNT, where each node/edge in the graph signifies the corresponding virtual node/link in the VNT and has a set of features. We denote node features by a three-dimensional matrix $F_n \in \mathbb{R}^{|V|,|V|,7}$, so that each node $v \in V$ is characterized by $|V|$ vectors of seven values. Here, V is the node set and $|V|$ gives the number of nodes in V. Each vector conveys the transmitter-side configurations for the connection from v to the corresponding destination node, which include launch power, bit rate, baud rate, channel spacing, number of channels, transponder type, and transponder mode. We embed the physical parameters of virtual links (i.e., total link length, number of spans, number of physical links) into edge features $F_e \in \mathbb{R}^{|E|,3}$.

2) Initialization. Having formed a graph data set $\mathcal{G}$, the algorithm then initializes null augmented node features F_a that have a similar shape to that of F_n but with three elements in each vector (*Line* 4). The three elements serve as placeholders for the subsequent aggregation of edge features. Meanwhile, we parameterize a feature embedder $h_{\theta_h}(\cdot)$ and a QoT predictor $g_{\theta_g}(\cdot)$ by neural networks [e.g., multi-layer perceptrons (MLPs)], where θ_h and θ_g are the sets of trainable weights.

3) Message passing and aggregation. Next, the for-loop covering *Lines* 5-14 performs iterative messages passing and aggregation for K layers, aiming at learning graph-level representations for each VNT (from nodes and edges to global). In each layer, every node $u \in V$ first collects the additions of the augmented node features of its adjacent nodes ($\tilde{F}_a[v]$) and the corresponding edge features ($F_e[E[u,v]]$) in *Line* 9. Here, *Line* 6 avoids the dissemination of updated node features within a single layer due to the sequential executions. *Lines* 10-14 are for message aggregation, ensuring that each vector of $F_a[u]$ is overwritten only when the received vector is not null, and it has not been updated before ($F_a[u][j] == \mathbf{0}$) or the path distance feature (w.l.o.g., placed as the first element) in the received vector is smaller than the current value. As such, we enable accumulations of edge features along the shortest routing paths for each node pair (connection). Note that, we disable the diffusion of node features F_n as lightpath QoT is less relevant to the transmitter configurations at immediate nodes. The accumulated features received by each node are fed to the feature embedder $h_{\theta_h}(\cdot)$ to extract higher-level representations, which are then combined with F_n to generate the graph representations $\mathcal{X}$ in *Line* 15. The above procedures distinguish the proposed GNN with a conventional design [37] that aggregates nodes indiscriminately and performs interleaving message passing and embedding.

4) Model outputs and training. *Line* 16 outputs the QoT estimations for all node pairs using $g_{\theta_g}(\cdot)$ and $\mathcal{X}$ as inputs. This way, we establish a generalizable QoT tool for VNTs of arbitrary structures. Finally, the algorithm returns a trained GNN by minimizing the discrepancy between the model predictions and the true labels Y in *Lines* 17-18, which will be detailed in Section 4.C.

B. Privacy Preserving with Distributed Collaborative Learning

A primary challenge for effective VNT management lies in the data confidentiality constraint, where neither substrate network managers nor tenants will disclose their respective network or service configurations in plain text. In this work, we consider a scenario in which substrate network managers provide optical tunnels (through optical line systems) to VNTs while tenants transmit data signals with their own optical line terminals. This leads to the separate ownership of node and edge features, i.e., by tenants and substrate network managers, respectively, making the proposed QoT estimator design not directly applicable. We bridge this gap by applying the distributed collaborative learning method presented in [30]. Fig. 2 illustrates the principle of distributed collaborative learning. Basically, each of the tenants and substrate network managers employs a customized neural network encoder (e.g., an MLP, which can be seen as an encryptor) to map the raw node/edge features into a latent space (i.e., encrypted features, *step 1*). Since neural networks consist of multiple layers of linear transformations interspersed with non-linear activation functions, retrieving the raw inputs from the latent space turns to an ill-posed inverse problem that cannot be accurately solved or even cannot be solved, especially in the absence of the knowledge about encoder structures. This principle underpins the autonomy of both entities. The VNT orchestrator collects the latent features (*step 2*) and executes Algorithm 1 (*step 3*) so long as it treats the latent features as the node/edge features. The encoders can be trained collaboratively

Algorithm 1. GNN-based network-wide QoT estimator design.

1: **Input**: graph data $\mathcal{G}$, number of aggregation layers K.
2: **Output**: network-wide QoT estimator $f_\theta(\mathcal{G})$.
3: derive the node set V, edge set E, node features $F_n \in \mathbb{R}^{|V|,|V|,7}$, edge features $F_e \in \mathbb{R}^{|E|,3}$, and labels $Y \in \mathbb{R}^{|V|,|V|}$ for each sample in $\mathcal{G}$;
4: initialize augmented node features $F_a \leftarrow \mathbf{0}$ ($F_a \in \mathbb{R}^{|V|,|V|,3}$), feature embedder $h_{\theta_h}(\cdot)$, and QoT predictor $g_{\theta_g}(\cdot)$;
5: **for** $i = 1$ to K **do**
6:     $\tilde{F}_a \leftarrow F_a$;
7:     **for** each node u in V **do**
8:         **for** each adjacent node v of u **do**
9:             $F' \leftarrow \tilde{F}_a[v] + F_e[E[u,v]]$;
10:             **for** $j \in [1, |V|] \setminus u$ **do**
11:                 **if** $F'[j] == \mathbf{0}$ **then**
12:                     **continue**;
13:                 **if** $F_a[u][j] == \mathbf{0}$ or $F'[j][0] < F_a[u][j][0]$ **then**
14:                     $F_a[u][j] \leftarrow F'[j]$;
15: $\mathcal{X} \leftarrow \{F_n, h_{\theta_h}(F_a)\}$;
16: $f_\theta(\mathcal{G}) \leftarrow g_{\theta_g}(\mathcal{X})$;
17: optimize $\theta = \{\theta_h, \theta_g\}$ to minimize the discrepancy between $f_\theta(\mathcal{G})$ and Y;
18: **return** $f_\theta(\mathcal{G})$.

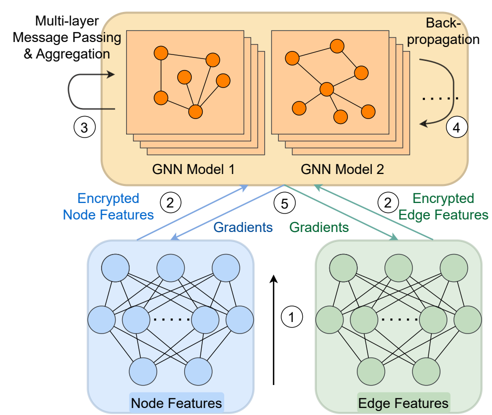

Fig. 2. Principle of distributed collaborative learning.

Table 2. SNR thresholds for different transceiver specifications (OpenROADM MSA ver. 5.0 versus Voyager) [38].

OpenROADM MSA ver. 5.0		Voyager	
Mode	SNR Threshold	Mode	SNR Threshold
100 Gbit/s, 31.57 Gbaud	12 dB	100 Gbit/s, 32 Gbaud	12 dB
200 Gbit/s, 31.57 Gbaud	20.5 dB	200 Gbit/s, 66 Gbaud	16 dB
200 Gbit/s, 63.1 Gbaud	17 dB	300 Gbit/s, 44 Gbaud	18 dB
300 Gbit/s, 63.1 Gbaud	21 dB	400 Gbit/s, 66 Gbaud	21 dB
400 Gbit/s, 63.1 Gbaud	24 dB		

with the GNN according to the chain rule [30], i.e., by tuning the GNN through back propagation (*step 4*) and distributing the gradients of the loss function with respect to the latent inputs to the encoders for further gradient updates (*step 5*), without specific modifications of the training algorithm adopted.

C. Meta-learning-aided Service Automation

Despite the proposed GNN-based QoT estimator design may learn generalizable graph representations, VNTs also involve nontopological characteristics, for instance, utilization of different modulation formats. This can severely degrade the performance of a trained model when directly applied to new tasks. Therefore, automating QoT estimation services for VNTs further entails training algorithms that can harness accurate QoT estimators for unseen VNT configurations promptly. In this work, we apply the model-agnostic meta-learning (MAML) algorithm [39] to accelerate the training of QoT estimators. The core idea of MAML is to learn model initialization (dubbed meta model) that can generalize over tasks, so that only a small number of samples are needed to fit the learned initialization to a target task. To do so, MAML constructs a support set $\mathcal{S}_t$ and a query set $\mathcal{Q}_t$ for each task t, i.e., the QoT estimation task for a given VNT. Specifically, $\mathcal{Q}_t$ contains the graph data sample for the target VNT, while $\mathcal{S}_t$ is composed of samples from VNTs of similar configurations (e.g., same topology but different lightpath parameters). During training, MAML first initializes a meta network, as for the proposed network-wide QoT estimator, $f_\theta(\cdot)$, and traverses all the tasks sequentially. For each task, MAML takes $f_\theta(\cdot)$ as a starting point and performs multiple rounds of gradient updates (using a conventional training algorithm, e.g., stochastic gradient descent) to minimize the loss on $\mathcal{S}_t$. Let $f_{\phi_t}(\cdot)$ denote the obtained model. Then, we evaluate $f_{\phi_t}(\cdot)$ with $\mathcal{Q}_t$ and obtain a loss of $\mathcal{L}(\phi_t, \mathcal{Q}_t)$. The objective of MAML is finding an optimal θ^* that minimizes the loss over all the tasks, i.e.,

$$\hat{\mathcal{L}}(\theta) = \sum_t \mathcal{L}(\phi_t, \mathcal{Q}_t). \tag{1}$$

The optimization problem translates into training a model initializer $f_{\theta^*}(\cdot)$, which achieves the best testing performance over all the tasks (minimized loss on the query sets) after fine tuning with the support sets. In practical implementations, the optimization is approximated by sequential updates on each task according to,

$$\theta = \theta - \alpha \cdot \nabla_{\phi_t} \mathcal{L}(\phi_t, \mathcal{Q}_t), \tag{2}$$

where α is the learning rate, $\nabla_{\phi_t}\mathcal{L}(\phi_t, \mathcal{Q}_t)$ computes the gradient of $\mathcal{L}$ regarding ϕ_t. After training, the VNT orchestrator can quickly provision QoT estimators to newly configured VNTs by fine tuning the meta model with a few additional samples.

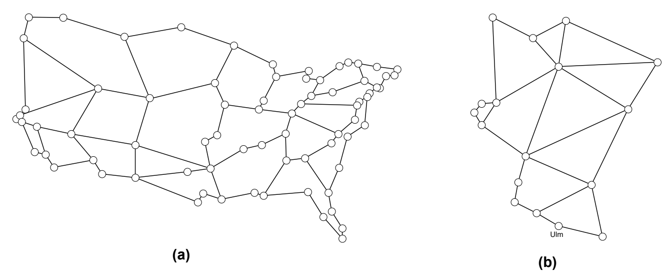

Fig. 3. (a) CONUS network and (b) German network.

Table 1. Properties of the CONUS and German topologies.

Property	CONUS	German
No. of Nodes	76	17
No. of Edges	99	26
Max. Path Len. (km)	6472.18	951.00
Mean Path Len. (km)	2069.20	317.89
Max. SNR (dB)	29.90	29.93
Min. SNR (dB)	9.08	17.36

5. PERFORMANCE EVALUATION

In this section, we first describe the data set used and then present performance comparisons between the proposed design and a baseline under different choices of parameters.

A. Data Generation

We evaluated the performance of the proposed design with synthetic data collected using GNPy [38]. Specifically, we con-

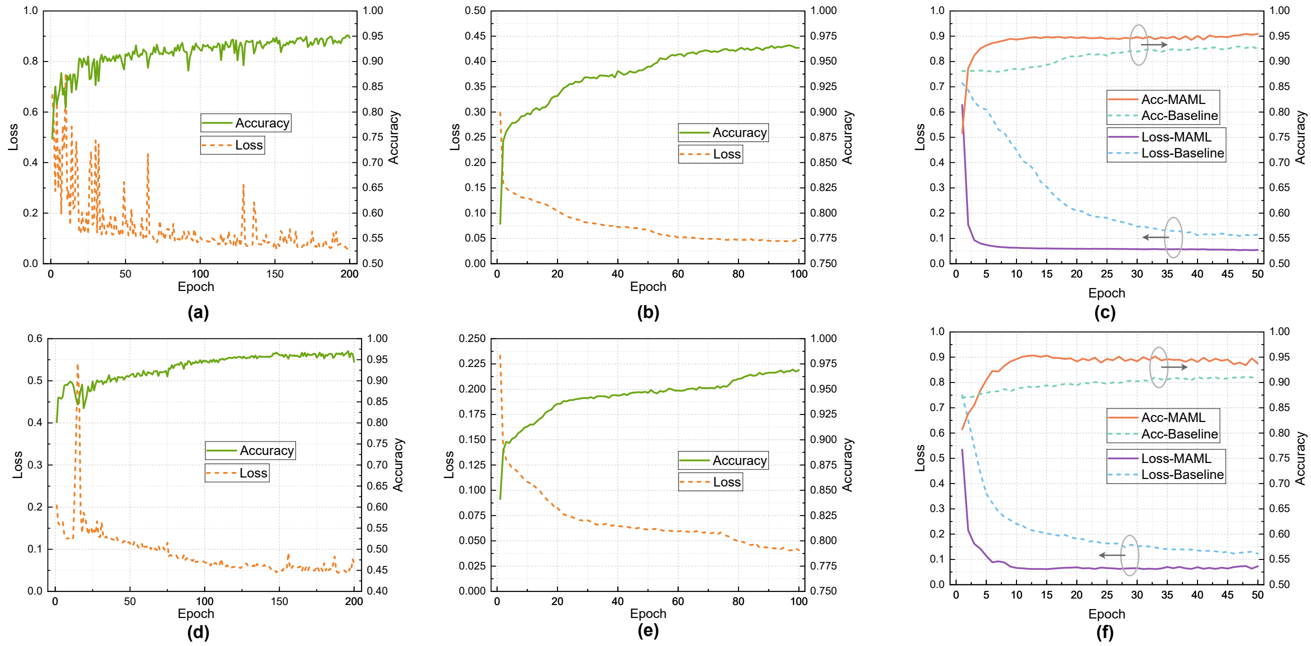

Fig. 4. Training loss & accuracy from (a) MAML ($K = 2$), (b) the baseline ($K = 2$), (d) MAML ($K = 3$), and (e) the baseline ($K = 3$); comparison of fine-tuning loss & accuracy between MAML and the baseline when (c) $K = 2$ and (f) $K = 3$.

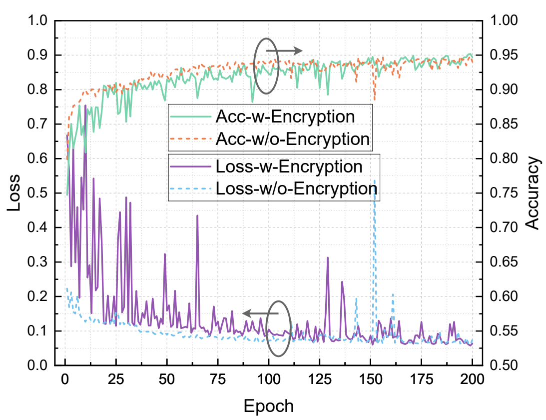

Fig. 5. Loss & accuracy with (w/) and without (w/o) feature encryption.

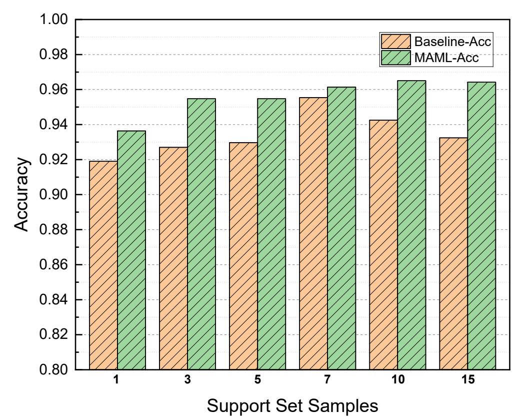

Fig. 6. Prediction accuracy as a function of number of fine-tuning samples in the support sets.

figured a large set of VNTs by embedding randomly generated graphs onto the CONUS and German network topologies as shown in Fig. 3. The main properties of the two topologies are presented in Table 1. Each VNT graph is composed of five to 30 virtual nodes, while the link mappings were computed based on the shortest path routing scheme. Within each VNT, we set up lightpaths with data rates, modulation formats and transmitter launch power randomly chosen from $\{100, 200, 300, 400\}$ Gbps, {QPSK, 8QAM, 16QAM}, and $[-2, 2]$ dBm, respectively. A flex-grid spectrum allocation mechanism was applied, which allocates spectrum ranges of 50 to 200 GHz at a granularity of 25 GHz to meet the data rate requirements. The signal-to-noise ratio (SNR) of each lightpath was monitored and compared with a preset threshold to determine the viability of the lightpath's QoT (i.e., "1" for viable communication, and "0" otherwise). Table 2 summarizes the SNR thresholds for the two transceiver specifications employed by GNPy. The configuration parameters and the viability indicators (labels) of these lightpaths, together with the adjacent matrix of the VNT graph, constitute a graph data sample. Then, the network-wide QoT estimation task for this specific VNT translates to binary classifications for all the lightpaths in the VNT.

B. Results and Discussions

1) Evaluation on the impact of number of aggregation layers. We first evaluated the impact of number of aggregation layers K on the performance of the proposed meta learning-aided network-wide QoT estimator design and a baseline that adopts the same GNN architecture but performs legacy training procedures (i.e., training a model by minimizing the loss over the entire training

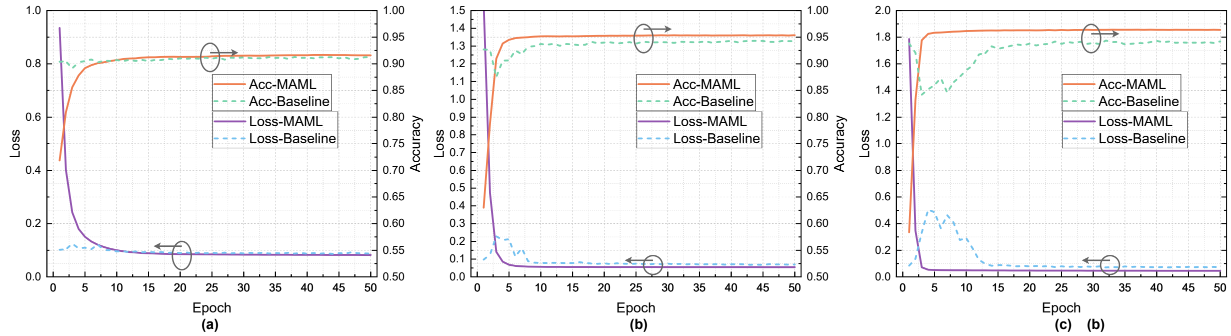

Fig. 7. Loss & accuracy results when fine tuned to larger VNTs with (a) $K = 2$, (b) $K = 3$, and (c) $K = 4$.

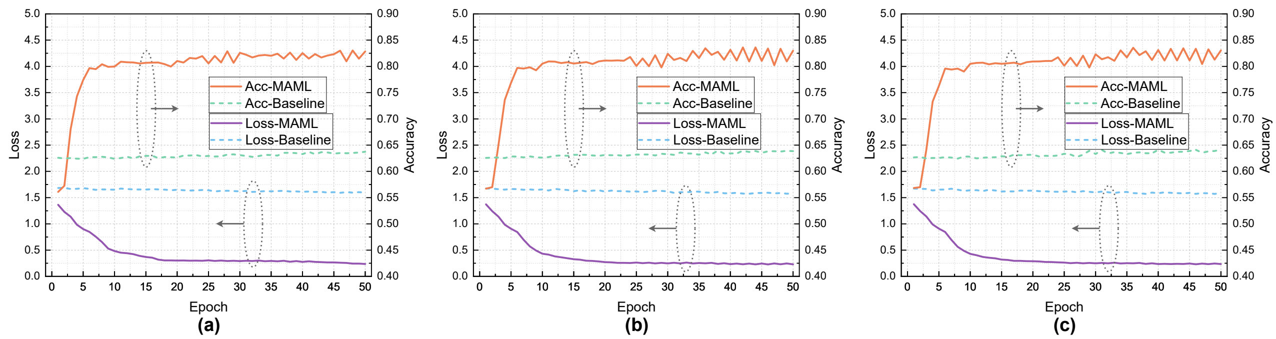

Fig. 8. Loss & accuracy results when pretraining and fine tuning were performed using VNTs generated under different substrate networks (CONUS versus the German topology) with (a) $K = 2$, (b) $K = 3$, and (c) $K = 4$.

set). The feature embedder and the readout module ($g_{\theta_g}(\cdot)$ in Algorithm 1) of the GNN were implemented by MLPs of two ([10, 7] and four layers ([24, 48, 12, 1]), respectively. In MAML pre-training, 200 tasks, each associated with a support set of five graph data samples and a query set of one sample, were used. Each graph sample contains five to 15 virtual nodes. The same data set was rearranged into a training set (with samples from the support sets) and a testing set (with samples from the query sets) for evaluating the baseline model. Figs. 4(a)-(b) show the evolution of loss and prediction accuracy in pre-training as a function of training epoch when K is equal to 2. Here, the loss and accuracy results were computed over the query sets (for MAML) or the testing sets (for the baseline). We can observe that the training process of MAML is less stable and the asymptotic accuracy is slightly lower (by $\sim 1\%$) compared with the baseline. The instability of MAML training can be attributed to the approximation with Eq. 2 which indirectly optimizes a meta model by applying the gradient of the loss of a task-specific model (fine tuned from the meta model) on a small query set. The indirect optimization also can be seen as computing second-order derivatives, leading to longer convergence periods. The accuracy disadvantage of MAML is owing to its objective of learning generalizable initializations for all tasks, whereas the baseline targets exactly fitting the training set. However, from Fig. 4(c), we can see that when fine tuned to provision QoT estimators for new VNTs (100 new tasks were generated), MAML converges faster and achieves an accuracy improvement by $\sim 3\%$ over the baseline, verifying the effectiveness of the learned meta model. Figs. 4(d)-(f) show the results when K was set to be 3, which coincide with the observations drawn when $K = 2$. Notably, we can see that a larger value of K results in more stable training and higher pre-training accuracy. This is because increasing K expands the receptive field of a node, allowing it to aggregate features from farther nodes, and thereby, achieves better topological awareness.

2) Evaluation on the impact of data encryption. Next, we discuss the impact of privacy preserving with distributed collaborative learning. The node and edge feature encryptors were both implemented by MLPs of two layers ([10, 5] and [20, 7], respectively). Fig.5 shows the training curves of MAML with and without feature encryption. The results indicate that introducing feature encryption does not compromise the asymptotic accuracy of MAML evidently and still leads to an accuracy of $\sim 95\%$ after convergence. The cost of feature encryption lies in the slightly worsen training stability and longer convergence time. This is attributed to the increased number of layers, which affects MAML especially because of the approximation used in training. Nevertheless, we believe this minor performance variation is acceptable provided the conservation of data confidentiality.

3) Evaluation on the impact of number of samples. With the pre-trained models mentioned above, we further assessed the impact of number of samples in the support sets on fine tuning (using 50 new tasks) and present the results in Fig. 6. Still, the baseline model was fine tuned with the same samples in the support sets. It can be observed that MAML consistently outperforms the baseline and that the performance of both designs improves with the size of support set. MAML can achieve an accuracy of $> 93\%$ with just one sample in the support set because the proposed GNN already learns generalizable graph presentations, and this performance is elevated to surpass 96% with seven samples.

4) Evaluation on model generalization ability over larger VNTs.

The above results demonstrate the generalization ability of MAML when fitted to new VNTs of the same scales. Next, we tested the generalization ability of MAML when provisioning QoT estimators for VNTs of larger scales. Specifically, we tried to fit a meta model trained previously with VNTs of $[5, 15]$ virtual nodes and $K = 2$ to VNTs of $[20, 30]$ nodes. Fig. 7 presents the results of loss and accuracy after fine tuning with K set to 2, 3 and 4, respectively. We can see that the proposed GNN allows both MAML and the baseline to quickly fit larger VNTs. Again, MAML outperforms the baseline in all three cases. The advantage of MAML gets more evident as K increases, despite that a larger value of K leads to a slightly higher initial loss (larger receptive fields, and thereby, a more complex model to be optimized). When $K = 4$, MAML achieves an asymptotic accuracy of 96.3% after training with ten epochs, while the asymptotic accuracy from the baseline is 94.1% at epoch 50. Besides, the training process from MAML remains more stable as K increases.

5) Evaluation on model generalization ability over different substrate networks. Ultimately, we evaluated the generalization ability of the proposed design in a more challenging setting, where model pretraining and fine tuning were performed using data collected from different substrate network topologies. In particular, we still used the previously pretrained models but fitted them to 50 VNTs generated under the German network depicted in Fig. 3(b). These VNTs are composed of five to ten virtual nodes. Note that, the German network allows for provisioning of larger-demand connections and the adoption of more advanced modulation formats owing to its smaller scale (shorter end-to-end distances), and thereby leads to different transmission characteristics. The results are presented in Fig. 8. In this setting, the proposed design dominates the baseline by achieving accuracy improvements of nearly 20%. MAML is able to converge after 20 training epochs, whereas the baseline fails to a large extent when adapted to the new tasks, achieving an accuracy of only around 63.8%. In contrast, the asymptotic accuracy from MAML is $\sim$ 82.5%. We also notice from Fig. 8 that the impact of increasing K is negligible. This is because the German network has a smaller graph radius, and therefore, $K = 2$ already provides a receptive field adequate for learning useful graph representations. Overall, the above results demonstrate superior generalization ability of the proposed design compared with the baseline.

6. CONCLUSION

In this paper, we presented a meta-learning-aided ML service automation framework for dynamic VNT configuration in optical networks. We studied a GNN-based network-wide QoT estimator design, complemented by a distributed collaborative learning mechanism, as a use case under the proposed framework. Numerical results demonstrate superior performance of the proposed design in terms of prediction accuracy and generalization ability. Future research directions include *(1)* developing joint optimization methods for VNT embedding and ML service provisioning, and *(2)* investigating meta learning approaches for automating the entire ML service provisioning pipeline.

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