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Transfer Learning for QoT Estimation in Time-Varying Optical Networks

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Abstract: QoT estimation is essential for efficient spectrum utilization and to minimize lightpath reconfigurations. However, the time-varying state of optical networks complicates this task. We explore transfer learning to adapt QoT models to evolving network conditions.

1. Introduction

In optical network deployments, the infrastructure properties vary over time due to events such as equipment aging, repairs, and replacements. This dynamic nature makes it challenging to maintain a detailed and up-to-date network inventory. In this scenario, quality of transmission (QoT) estimation based on analytical models suffers due to the need for precise and up-to-date knowledge of the network parameters. Even minor inaccuracies in QoT estimation can significantly impact network performance, leading to unnecessary lightpath reconfigurations due to overestimations or spectrum underutilization due to underestimations. Machine learning (ML) approaches such as artificial neural networks (ANNs) have demonstrated high accuracy even with uncertain data [1], but also suffer from performance degradation due to network variability. Transfer learning (TL) has been applied to transfer knowledge from a source to a target domain, offering reduced training time and lower data requirements compared to training from scratch [2, 3], but only recently applied to mitigate the issues that arise from time-varying networks [4].

In this paper, we investigate how transfer learning can reduce the computational complexity of the ML training, and the overall ML lifecycle, while maintaining accuracy comparable to that of a model fully retrained on a larger dataset. Furthermore, we propose a hybrid method that combines transfer learning and retraining, offering a trade-off that ensures long-term accuracy at a modest increase in complexity. The proposed method maintains the model accuracy while reducing the cumulative complexity for the entire model lifecycle by a factor of 9-fold.

2. Proposed Transfer Learning Method for QoT Estimation and Simulation Setup

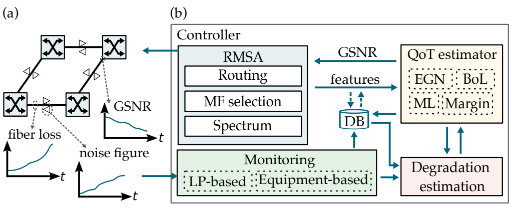

Fig. 1: System overview; (a) optical network; (b) network controller.

We study the dynamic routing, modulation, and spectrum assignment (RMSA) problem over a time-varying elastic optical network (EON) to evaluate the impact of different QoT estimation methods on the overall network performance. Fig. 1 presents a system overview in which the EON is considered with time-varying parameters. Specifically, two parameters are subject to change over time: the amplifier noise figure increases due to equipment aging, and fiber loss increases due to additional splicing from fiber repairs. The QoT of each lightpath (LP) is monitored at the receiver. In our RMSA approach, the k-shortest-path first-fit algorithm is used to select the routing path and assign the spectrum. A QoT estimator is employed to select the modulation format (MF), which can be determined using analytical formulas, beginning of life (BoL) network parameters, or ML models. The estimator returns the generalized signal-to-noise ratio (GSNR) based on a set of input characteristics and network parameters. Each QoT, along with its corresponding input features and the actual monitored QoT after LP provisioning, is stored in a database. The mismatch between the estimated and actual QoT is used to assess whether the QoT estimator requires an update.

In the simulations, we use the European network topology, which consists of 26 nodes and 42 links, and compute k=5 shortest-paths. The ground truth (GT) is computed using the enhanced Gaussian noise (EGN) model, assuming complete and up-to-date knowledge of all network parameters over time. We propose an ANN as the QoT estimation tool, employing the architecture described in [4]. The ANN takes 17 input features related to node, lightpath, and path characteristics. It includes a single hidden layer with 256 neurons and uses the tanh activation function. The ANN estimates the GSNR, which is then used to select the MF within the RMSA process. We consider five modulation formats: QPSK, and 8-, 16-, 32-, and 64-QAM, with their respective GSNR thresholds set to 6.72, 10.84, 13.24, 16.16, and 19.01 dB. The dataset used to train the ANN initially consists of 100,000 connection requests, generated under the assumption of BoL network parameters. For each request, the RMSA is executed using the EGN model to determine the LP and select the appropriate modulation format.

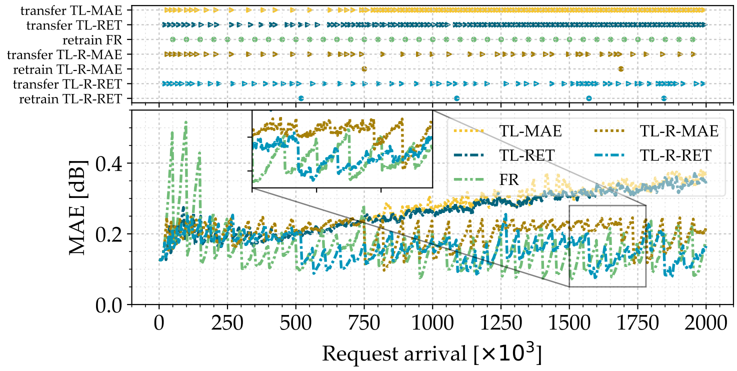

Fig. 2: Transfer learning/retraining triggered (top), and mean absolute error (MAE) (bottom) of proposed QoT estimation strategies over time.

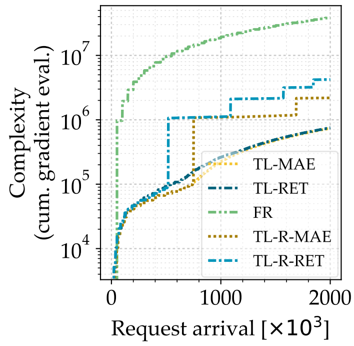

Fig. 3: Complexity of proposed QoT estimation strategies over time.

To evaluate the impact of time-varying network parameters, we simulate 2 million connection requests. Request arrivals follow a negative exponential distribution with a mean inter-arrival time of 3 minutes and an average holding time of 7 hours. Source and destination nodes are randomly selected for each request. Network parameter variability is introduced, on average, every 5 hours. During each variability event, the noise figure of a randomly selected amplifier increases by [0.1, 0.5) dB. Additionally, the attenuation of a randomly selected fiber span increases by [0.05, 0.1) / s_l, where s_l denotes the length of the span.

We consider 5 ML-based methods for QoT estimation. The FR method retrains the ANN from scratch using the most recent LPs information, triggered every 50,000 request arrivals. TL-MAE and TL-RET use TL to update the ANN. TL-MAE is triggered when the mean absolute error (MAE) exceeds a predefined threshold t_{mae}. TL-RET is triggered when the number of allocation retries per 1,000 lightpaths exceeds a threshold t_{ret}. In both cases, TL is applied by freezing the neurons in the hidden layer of the ANN and updating only the output layer. In this paper, we propose TL-R-MAE and TL-R-RET, which combine both TL and retraining. Similar to the previous approaches, TL is triggered when the respective threshold is violated. However, if the threshold is exceeded again within fewer than t_{tl} additional request arrivals, the ANN is retrained from scratch instead of applying TL. The threshold values are set as follows: t_{mae}=0.25, t_{ret}=0.1, and t_{tl}=10,000. The number of training epochs is set to 200 for training from scratch, and 20 for TL updates.

3. Results and Conclusions

Fig. 2 (bottom) shows the MAE over time for the evaluated QoT estimation methods. Fig. 2 (bottom) shows the retraining or TL event occurrences. MAE consistently decreases following retraining and TL update events. For the TL-based methods (TL-MAE and TL-RET), the magnitude of improvement from each transfer event diminishes over time, as the network state diverges from the initial state. In contrast, the FR method exhibits consistent, periodic reductions in MAE, independent of network state variations, due to the full retraining. The performance of the proposed hybrid methods (TL-R-MAE and TL-R-RET) also degrades over time but shows significant improvement after retraining events. This is particularly evident in the zoomed-in inset of the figure: at $1,571 \times 10^3$ requests for TL-R-RET and $1,688 \times 10^3$ requests for TL-R-MAE. The average MAE is 27.1%, 26.1%, 15.8%, 20.1%, 15.9%, for TL-MAE, TL-RET, FR, TL-R-MAE, TL-R-RET, respectively. These results demonstrate that TL-R-RET achieves performance comparable to the full retraining (FR). Fig. 3 illustrates the lifecycle computational complexity of each method, measured by the cumulative gradient evaluations during training. FR has the highest complexity, as it involves updating all ANN weights every retraining event. The TL-only methods (TL-MAE, TL-RET) exhibit the lowest complexity, since only the output layer is updated. The proposed hybrid methods (TL-R-MAE and TL-R-RET) show a slight increase in complexity compared to the TL ones. They balance performance while reducing computational cost by a factor of 9 compared to the retraining method.

In conclusion, this work investigates the trade-offs of combining transfer learning (TL) with full retraining for QoT estimation in time-varying optical networks. The results show that the proposed hybrid methods can achieve accuracy comparable to full retraining approaches, while significantly reducing computational complexity.

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