On Advantages of Traffic Prediction and Grooming for Provisioning of Time-Varying Traffic in Multilayer Networks

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***Abstract*—The constantly increasing traffic volume triggers the fast development of new optimization methods for backbone optical networks. Operators seek new ways to improve several network performance metrics, including network stability. In this paper, we propose a multilayer packet-over-optical approach combining grooming and traffic prediction. We demonstrate the advantages of the proposed algorithm for provisioning daily time-varying traffic of various services through multiple metrics. We show how the proposed approach, enabled by the cross-layer information exchange, can achieve a served traffic increase of about 26% in operational scenarios.**

***Index Terms*—multilayer network, grooming, traffic prediction**

I. Introduction

The development of new technologies and the rising popularity of network-based services constantly and relentlessly increase the traffic volume in backbone networks [1]. New optimization methods are developed to cope with the inevitable *capacity crunch* and fit more traffic within the existing infrastructure. Multilayer application-aware network optimization [2], [3] is one of the recent promising approaches in which the traffic from various services is provisioned using cross-layer information exchange. On top of bandwidth blocking probability minimization, serving the traffic of different types in multilayer networks can bring benefits in multiple measures, such as quality of service (QOS) assurance [4] or provide a balance between costs and delay constraints [5].

An approach often considered in multilayer networks is traffic grooming; the aggregation of traffic from multiple low-rate connections from the upper layer into high-rate optical channels allows several independent traffic streams to share the bandwidth of a lightpath. That way, by maximizing the amount of traffic on each lightpath, it is possible to minimize the number of lightpaths, which can lead to energy savings [6]. Recent works also show how combining multiple IP requests into large optical channels through traffic grooming can reduce bandwidth blocking and fragmentation [7], [8].

Furthermore, machine learning (ML) techniques are gaining attention in optical networking [9], [10], further enhancing optimization algorithms. Developed models provide valuable information of various kinds, including quality of transmission estimation [11], [12] or link dimensioning [13]. Considering the time-varying and constantly increasing nature of network traffic, one of the essential research directions is using traffic prediction. The knowledge about future traffic can improve the request routing decisions and decrease overall bandwidth blocking probability and resource usage in the short term [14]–[17] or enable gradual cost-minimizing network upgrade in the long term [18].

In this paper – as the main contribution and novelty – we propose new multilayer network optimization methods for time-varying traffic of various services and applications. We demonstrate the advantages of cross-layer information exchange to perform traffic grooming and use free bandwidth in the existing lightpaths for provisioning additional connection requests. Furthermore, we propose to employ traffic prediction to improve grooming decisions and demonstrate its benefits through multiple metrics. We show how our machine-learning-aided algorithm achieves lower bandwidth blocking, optimizes resource utilization, and makes much fewer reallocations, leading to more stability and potentially lower operational costs. Additionally, we describe a time-varying traffic model using real-life traffic patterns of various network-based applications. We perform simulations using realistic, up-to-date assumptions to demonstrate the operation of our proposed algorithms and collect several statistics to provide more insight into the obtained results.

The paper is organized as follows. Related works are described in Section II. The network model is introduced in Section III, followed by the description of proposed algorithms in Section IV and the traffic model in Section V. Finally, the numerical experiments and results are presented in Section VI. Section VII concludes this work.

II. Related Work

Multilayer network optimization is not a new topic and has been addressed by many researchers in the last few years. The most recent research works include algorithms for real-world networks approaching capacity limits. The authors of [4] proposed an application-aware degradation scheme to ensure the provisioning of the most critical connections. Similarly, the authors of [5] focused on provisioning the most latency- and protection-sensitive requests before the less urgent, best-effort traffic. On the other hand, the authors of [19] did not distinguish specific traffic classes but proposed a mechanism of

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hiding certain parts of network resources for unexpected traffic bursts and showed how it decreases the overall bandwidth blocking probability. Moreover, the authors of [20] used the cross-layer information exchange to balance congestion probability and reconfiguration frequency. Finally, traffic grooming of IP requests into optical channels was addressed by the authors of [8] together with fragmentation-awareness, achieving bandwidth blocking probability reduction.

Several works also demonstrated the benefits of using traffic prediction for network operation. The most recent research showed how forecast-based routing path selection can bring benefits in lower blocking probability [15], [16]. The authors of [21] showed how the benefits of using traffic prediction are marginal in a normal network state but increase under heavy traffic load. In [22], the benefits of using traffic prediction were presented in conjunction with dedicated path protection. Furthermore, provisioning of time-varying traffic was addressed in [23], where the authors showed the advantages of periodic reallocations of daily traffic of various services to minimize bandwidth blocking. Additionally, the authors of [24] and [25] used traffic prediction for periodic re-routing to minimize congestion on network links. However, above described research only considers the optical layer.

To the best of our knowledge, current literature lacks research regarding the combination of traffic prediction and grooming in multilayer networks. To fill this gap, we propose novel algorithms, demonstrating their benefits through multiple metrics. We show how the cross-layer information exchange aided by ML can improve various measures, including bandwidth blocking, resource usage, and the number of required reallocations.

III. Network Model

We assume that the multilayer network consists of a packet layer and an optical layer. The packet layer is used to directly serve the services and applications, i.e., to establish requests/connections required to serve various types of services and applications. In turn, the optical layer is used to create a virtual topology of lightpaths transmitting aggregated requests. We assume that the requests in the packet layer represent time-varying traffic, i.e., traffic that changes over time (day) due to the different popularity of various services and applications at different times of the day. For instance, Fig. 1 shows hourly trends for a popular system, namely TikTok, based on [26].

The optical network operates on flexible (elastic) frequency grid with slots (slices) of 12.5 GHz granularity and with coherent transceivers (TRXs), which support reconfigurable bitrates and apply various modulation formats (MFs) according to the optical path properties. We use Ciena WaveLogic 5 Extreme [27] transceiver model. The below presented parameters are based on various information provided by Ciena. In more details, the TRXs support one of the two available baudrates (64 or 95 Gbaud). In turn, each TRX supports an optical channel (OC) of 6 or 9 slices (75 or 112,5 GHz, respectively). The bitrates carried by OCs depend on the spectral efficiency of the MF in use. If a request surpasses the maximum capacity that a TRXs can support using a particular MF, the request is established with the use of superchannel (SCh) occupying a relevant number of adjacent slices. The transmission reaches of considered modulation formats are provided in Table I.

TABLE I: Modulation formats – transmission reach and supported bitrate based on [27].

MF	transmission reach	supported bitrate	# slots
QPSK	no limit	200G	6
8QAM	no limit	400G	9
16QAM	800 km	400G	6
16QAM	1600 km	600G	9
32QAM	200 km	800G	9

The requests are served in the packet layer. With the assumed time-varying traffic, the bitrate of each request changes every time step.

IV. Proposed Algorithms

The first proposed multilayer algorithm, MLTL, assumes a dedicated lightpath for each time-varying connection request. First, the requests are sorted by their current bitrate descending. Then, lightpaths are created in the optical layer for each request, according to their current bitrate. In each subsequent time step, the requests are sorted by current bitrate and ensured that they still fit in their lightpaths. For each request no longer fitting, its lightpath is torn down, and a new one is created according to the current bitrate. In turn, the number of lightpaths in the optical layer is constant and equal to the number of requests. This algorithm serves as a baseline solution, corresponding to traditional dynamic traffic algorithms for optical networks with individual lightpaths for traffic demands. Note that the packet layer does not have the topology details of the underlying optical network and only sends lightpath creation or tear-down requests, receiving information about their supported bitrate. In turn, the packet layer is a virtual topology of lightpaths.

In the optical layer, after receiving a lightpath creation request from the upper layer, a new lightpath that satisfies the specified bitrate is sought using a greedy algorithm. For a given pair of the request's source and destination nodes, a set of 10 shortest candidate routing paths is considered, which enables a high probability of setting up a lightpath without unnecessary algorithm complexity increase. The most spectrally efficient MF is selected on each path, supporting its transmission distance. The number of required slots is computed supporting the requested bitrate. For the obtained number of slots, a SCh satisfying spectrum continuity and contiguity constraints is sought with the lowest possible ending slot index. Finally, corresponding SChs found on each candidate path are compared, and the one with the lowest ending slice index is selected to serve the request. Note that due to the TRXs model, the bitrate supported by the lightpath may be larger than the requested bitrate. Therefore, the information regarding created lightpath capacity is returned to the upper layer.

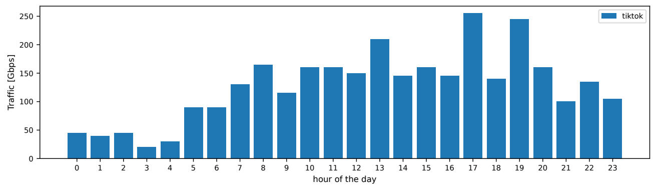

Fig. 1: TikTok original.

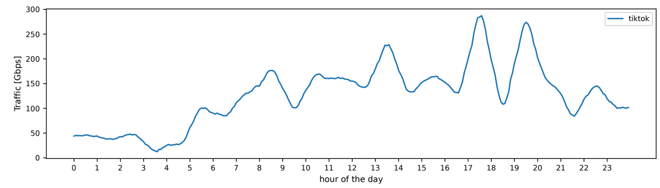

Fig. 2: TikTok with 5 minutes interpolation and Gaussian noise.

In a proposed modification to the baseline MLTL algorithm, we take advantage of the cross-layer information exchange and use traffic grooming. In more detail, the optical layer uses transceivers to create lightpaths with certain capacity granularity, thus rounding the requests bitrate up and leaving some unused free bandwidth. The connection requests often have a relatively small bitrate and can be fit in those free spaces without the need to set up additional lightpaths. Therefore, in MLTL_G, the algorithm first tries to incorporate the requests sorted by bitrate in existing lightpaths in each time step, using the information about the remaining free bandwidth obtained from the optical layer. Moreover, using Yen's algorithm, five candidate paths of multiple lightpaths are created for the requests if they do not fit in any existing direct lightpath from their source to their destination node, thus employing IP routing. The candidate paths are sorted by length measured in the number of lightpaths. The chosen $k = 5$ prevents the creation of longer paths in the top layer, as they would require multiple O–E–O conversions. In the end, if a request cannot be provisioned in the current lightpath topology, a new lightpath is created for it. Note that the described procedure is used not only for the initial allocation but also when reallocating requests that no longer fit, except for the initial iteration, when no routing in the packet layer is allowed. Moreover, in each iteration, the requests with a bitrate lower than the previous time step are considered first to free resources for the ascending bitrate of the remaining connections.

Finally, in MLTL_GP, we employ short-term traffic prediction to handle request allocation and reallocation better, considering their forecasted bitrate. In more detail, if a request is predicted to have an increasing traffic trend in the next timestep, the algorithm makes decisions using the maximum of the request's next three bitrates instead of the current one. That way, more bandwidth is reserved for the forecasted bitrate increase, and additional, tightly fitting requests are not groomed into its lightpath, hopefully preventing unnecessary reallocations. The length of the considered prediction horizon was tuned in preliminary experiments.

The overview of request allocation in a considered multi-layer network is visualized in Fig. 3. Let us consider an optical network topology with 5 nodes $V = \{v_1, \ldots, v_5\}$ and 7 links (edges) $E = \{e_1, \ldots, e_7\}$ (Fig. 3a). To accommodate various requests from the packet layer, lightpaths are created in the optical layer. In Fig. 3b, different colors represent different lightpaths $L = \{l_1, \ldots l_6\}$ with assigned spectrum resources on adequate network links. Typically in optical networks, spectrum continuity constraint is required, where each lightpath is operating on the same frequency window along the routing path. The routing of each lightpath in the optical network is presented in Fig. 3c, where each color represents a different lightpath $l \in L$. Based on that, a packet (virtual) network topology is created where each lightpath represents an edge between its end nodes (Fig. 3d). Note that a given pair of nodes may have more than one link in virtual topology, depending on how many lightpaths are available between the given pair of nodes. Moreover, different lightpaths set up between a pair of nodes in the bottom layer might use different routing paths. Nevertheless, they are equivalent to the top layer. Fig. 3e presents the allocation of some new incoming requests r_1 and r_2 between nodes v_3 and v_4 during network operation, each requiring 100 Gbps bandwidth. The chart visualizes the occupied bitrate in each lightpath $l \in L$, i.e., a bitrate that is assigned to other requests (blue-gray color). Assuming that the request r_1 (yellow) is processed, the algorithm seeks an available link in the virtual topology to accommodate its bitrate. In particular, if grooming is considered, lightpath l_4 contains sufficient residual capacity. In such a case, the allocation algorithm accommodates (grooms) request r_1 to that lightpath. Next, request r_2 (green) is processed. As there are not enough available resources in lightpath l_4, the algorithm can either request from the optical layer to create a new lightpath between nodes v_3 and v_4 or can use Yen's algorithm to find different routing path in the virtual topology. In the considered example, the routing path consisting of lightpaths l_3 and l_5 is selected. Note that using a multi-hop routing path in the virtual topology may require optical-electrical-optical conversion in the intermediate node that introduces additional latency and some optical links might be traversed twice. Nevertheless, the introduction of routing in the packet layer allows for accommodating more traffic compared to single-hop path creation. It is worth noting that the algorithm without grooming requires the creation of a new lightpath for each incoming request in the packet layer.

V. TRAFFIC MODEL

The traffic is generated based on data from [26], differentiating daily patterns of eight diverse traffic types associated with popular network-based applications, including, e.g., YouTube, TikTok, and Zoom. Requests are generated with bitrate scaled to the 100-150 Gbps range with a uniform distribution. Each request has a traffic pattern of a specific application, and there are multiple requests for each pair of nodes. Since [26] only provides hourly means of the bitrate of particular traffic types, an interpolation algorithm is employed to obtain traffic values every five minutes, which gives 288 observations per day. In

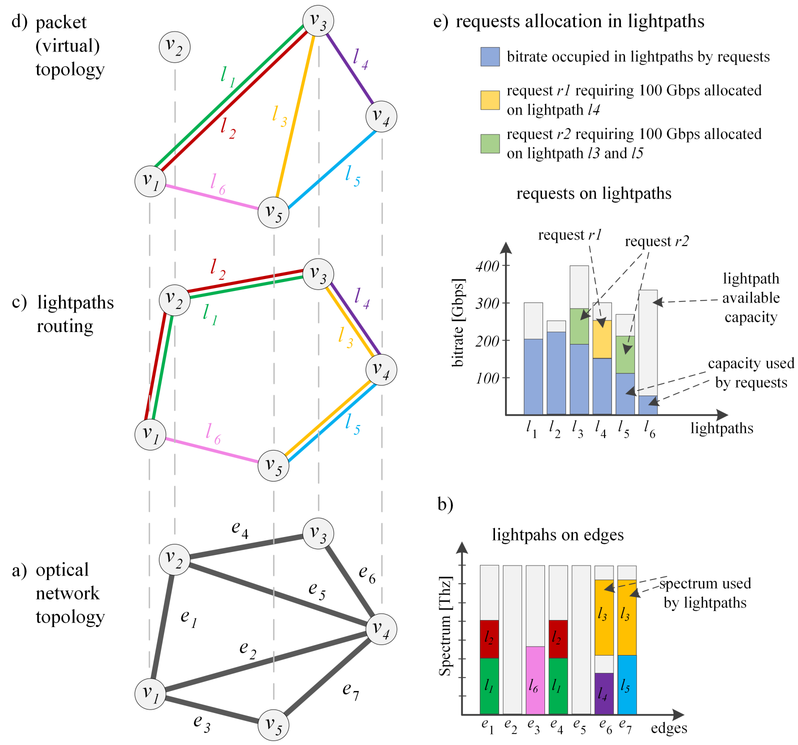

Fig. 3: Overview of requests allocation in multilayer network.

particular, between each hour, a signal is interpolated using a combination of linear and exponential functions such that the integral for a given hour remains the same as in the original data. Further, Gaussian noise is introduced to the signal to recreate more natural traffic changes behavior. Fig. 1 and 2 present the original TikTok signal and a signal with applied 5 minutes interpolation, respectively.

The traffic prediction model is based on our previous work [28]. In a nutshell, because of a high seasonality present in optical networks, each request's future exact bitrate values are based on two significant historical observations: the traffic a day and a week before the forecasted sample. Following the recommendation from [28], the ML algorithm of choice is linear regression as a fast and reliable predictor of highly seasonal network traffic. The prediction model is trained on one month-worth of traffic data for each request.

VI. Numerical Experiments

In the following part, we analyze averaged results of ten simulations of 24 hours of network usage, with bitrate changes every 5 minutes. The experiments are conducted for the US26 topology (see Fig. 4).

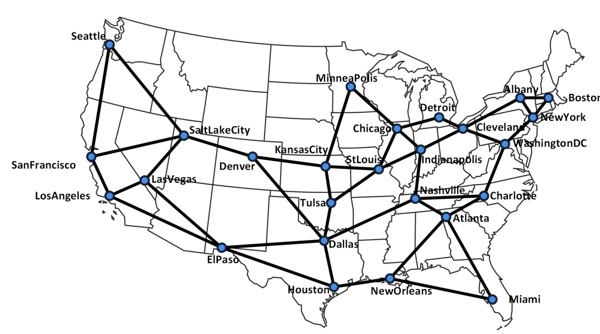

Fig. 4: US26 topology.

Fig. 5 presents the average highest occupied slot for each network link. This measure illustrates how evenly the traffic is distributed across the network. A humble but clear advantage of using traffic prediction is visible. The 320 slots available in each link are approached faster in algorithms without knowledge about future traffic. Furthermore, Fig. 6 presents the sum of occupied slots, which illustrates the usage of the available resources. It can be noticed that traffic grooming enables the creation of fewer lightpaths to serve the traffic. Traffic prediction further optimizes resource utilization, with noticeably fewer occupied slots at any of the considered traffic loads. Overall, the resource usage clearly but modestly benefits from traffic prediction and grooming. However, this is not the case for the number of reallocations, shown in Fig. 7, which measures the network's stability. As can be captured from the plot, the increase in traffic load leads to an higher number of required reallocations in MLTL, which uses individual lightpaths for each request. The usage of traffic grooming enables considerably fewer lightpath reallocations with a much slower increase under heavier traffic load, ensuring more stability. The use of traffic prediction further reduces the number of necessary reallocations, enabled by more informed algorithmic decisions. Note that an increasing traffic load further highlights the benefits coming from traffic prediction. In particular, for traffic of 41.25 Tbps, MLTL_G, and MLTL_GP need 5.7 and 11.9 times less reallocations than the reference MLTL.

Moreover, we want to underline that reducing the number of reallocations also contributes to decreasing the network operational costs (OPEX).

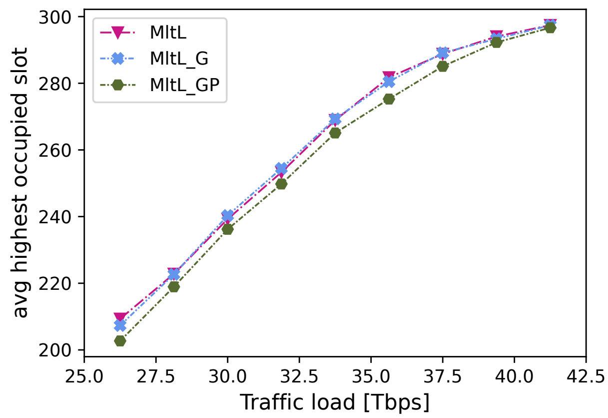

Fig. 5: Average highest occupied slot.

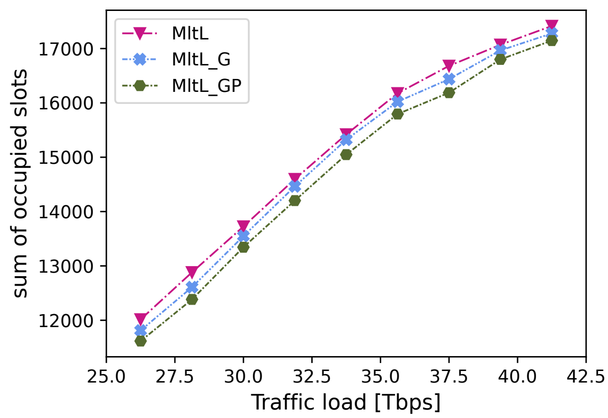

Fig. 6: Sum of occupied slots.

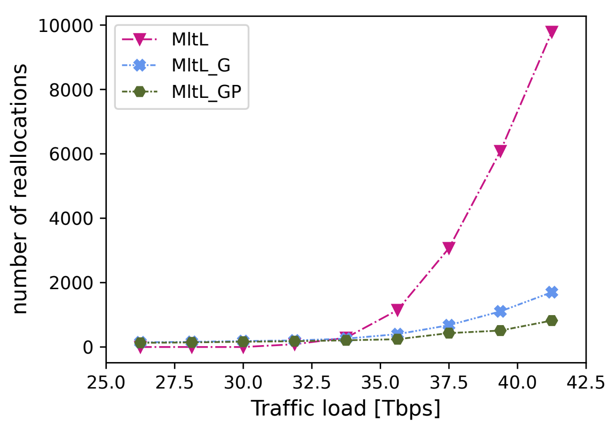

Fig. 7: Number of reallocations.

Fig. 8 reports bandwidth blocking probability (BBP), measuring what portion of the traffic was not provisioned under a specific load. Furthermore, to differentiate the blocked requests, in Fig. 9, we report BBP scaled by distance (BBP_SD), and in Fig. 10 BBP scaled by the square root of distance (BBP_SSRD). The motivation for using two additional blocking metrics is that the basic BBP does not account for rejected traffic being related to node pairs of various distances. As an example, in the considered network topology, the shortest distance between a node pair is 188 km, while the longest distance between a node pair (measured as the length of the shortest path) is 5894 km. Scaling the BBP by distance (Fig. 9) and the square root of distance in (Fig. 10) presents more insight into the performance of the compared approaches.

Clear benefits from traffic grooming are visible, with blocking occurring under a much heavier traffic load. Traffic prediction enables further BBP reduction. In more detail, the amount of accepted traffic assuming BBP of 1% is 34.99 Tbps, 41.04 Tbps, and 44.11 Tbps, for MLTL, MLTL_G, and MLTL_GP, respectively. It means that MLTL_GP allows to provision 26.1% and 7.5% more traffic in the network than MLTL and MLTL_G, respectively. The corresponding differences for the remaining BBP versions are similar. However, scaled BBP measures highlight the benefits of traffic forecasting more clearly. That means the use of or ML-aided algorithm led to the rejection of some more distant connections, thus accepting more short-term requests using shorter paths.

The average simulation time of 24h network usage with 5-minute sampling on a machine with the Intel Core i5-1038NG7 processor and 16 GB of RAM is 432ms for MLTL, 479ms MLTL_G and 502ms for MLTL_GP, with the number of reallocations accounting for the majority of the algorithm's complexity.

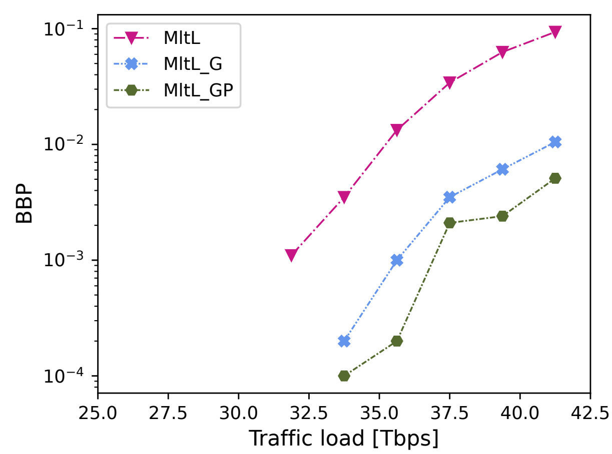

Fig. 8: Bandwidth blocking probability (BBP).

In summary, traffic grooming in multilayer networks enables the operators to fit considerably more traffic in a backbone network than traditional dedicated request lightpaths. Adding traffic prediction further improves network operation, leading to reduced blocking probability and resource utilization. The use of machine learning also substantially lowers the number of required reallocations, thus enabling OPEX decrease and stability improvement.

VII. CONCLUSIONS

In this paper, we tackled the problem of provisioning time-varying traffic in multilayer packet-over-optical networks.

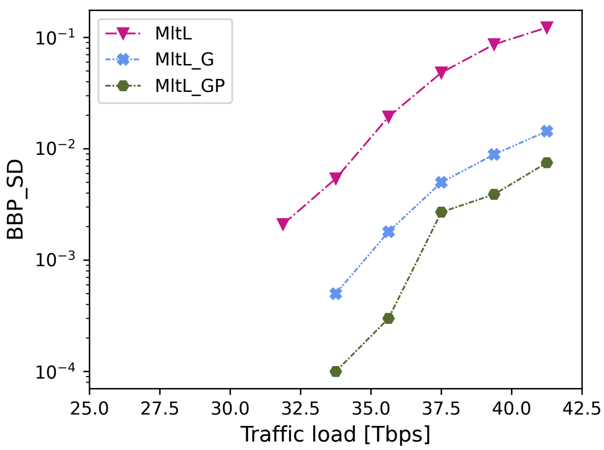

Fig. 9: BBP scaled by distance.

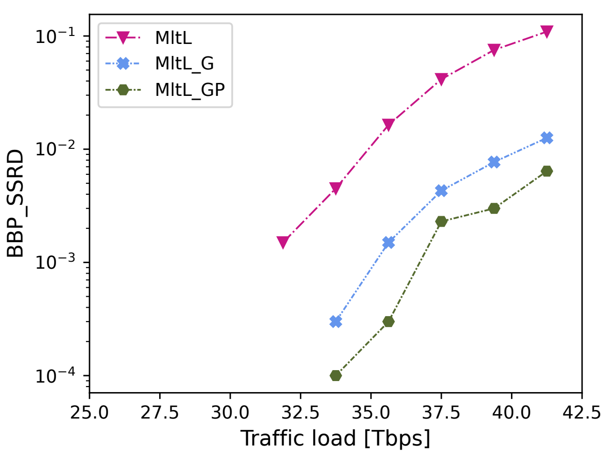

Fig. 10: BBP scaled by square root of distance.

Through experiments with connection requests of diverse traffic types, we demonstrated the advantages of using traffic prediction and grooming enabled by cross-layer information exchange in several metrics. Our algorithm, through the combination of grooming and ML-based traffic prediction, achieved a considerable reduction of bandwidth blocking, resource utilization, and the number of required reallocations. Gained benefits can improve network stability and lower OPEX while provisioning more traffic within the existing infrastructure.

In the future, we plan to use data analytics to create intent-based multilayer network optimization methods and consider the unique requirements of various traffic types.

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