Impact of Time-Varying Traffic Type on the Performance of Multilayer Networks

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***Abstract*—Traffic in backbone networks is characterized by strong seasonality, with clear patterns visible in various services and applications based on their usage throughout the day. Data-driven networks can learn these patterns to manage resources more efficiently as they become increasingly saturated. In this paper, we explore the benefits of traffic prediction and grooming across different traffic patterns. To achieve this, we simulate network operations using uniform sets of time-varying connection requests, where all demands in a simulation share the same traffic pattern related to a specific network-based service or application. Our goal is to thoroughly evaluate the robustness of the proposed techniques across diverse scenarios. The results will facilitate the design of future application-aware algorithms for the most efficient handling of each traffic pattern.**

***Index Terms*—multilayer network, application–aware network, machine learning.**

I. Introduction

Multilayer application-aware networks are an emerging approach in the current trend of building new, data-driven network optimization algorithms [1], [2]. With the significant advancements in network telemetry, vast amounts of measurements and information are now being collected [3], [4]. This data can be analyzed to identify patterns and enhance network operations through gained insights. Moreover, networks can utilize these learned patterns to dynamically self-optimize according to changing traffic conditions, which is a key aspect of intent-based networking [5], [6].

Traffic in backbone networks is a collection of numerous smaller connections of various types. With the growing popularity of network-based services and applications, a substantial portion of this traffic comes from data centers. Thanks to the aggregation of connections and the separation of data centers, clear daily and long-term trends and patterns for each service can be identified (e.g., see [7]). These patterns can be learned by machine learning (ML) algorithms, and the insights gained can enhance the development of new, intelligent algorithms through the use of traffic forecasting and other techniques [8], [9]. The possible applications of the traffic type identification and differentiation include traffic scheduling or downgrading non-crucial connections [10], [11].

As newly deployed solutions must be thoroughly tested before being applied in real-world networks, their functionality is first evaluated using simulators or network digital twins [12], [13]. During this process, multiple metrics of interest are collected to further refine the developed approaches and conduct a "what-if" analysis. These experiments often reveal intriguing dependencies and inspire new ideas.

In this paper, as the main contribution and novelty, we examine how various traffic patterns impact the performance of multilayer networks aided by artificial intelligence. To achieve this, we simulate network operations under uniform sets of requests, each containing demands corresponding to a specific popular network-based service or application. We explore the effects of changing traffic patterns across various metrics to quantify the benefits of utilizing traffic prediction and grooming. We repeat our investigation on two large topologies and reveal common and diverse trends. The obtained results shed light on in which cases traffic prediction and grooming give the clearest benefits and can be a guideline for creating new application-aware approaches.

The remainder of this paper is organized as follows. Section II describes the network and traffic model together with the multilayer network optimization algorithm. Section III provides an overview of our simulation setup and Section IV discusses the results we obtained. Finally, Section V concludes this work.

II. Network model and allocation algorithm

In this Section, we provide the overview of our network and traffic model, and describe the routing and resource allocation (RSA) algorithm we use.

We consider a two-layer network model with a physical Elastic Optical Network (EON) topology at the bottom and a virtual packet (IP) layer at the top. The upper layer is a virtual topology of lightpaths set up in the physical network. The layers are optimized jointly, exchanging information about the free and used bandwidth, and enabling traffic grooming. The connection requests to be provisioned are characterized by their source and destination nodes and a series of bitrates varying throughout time. The main assumptions of our network model are illustrated in Fig. 1. For more details see [14].

The dynamic traffic model comprises time-varying connection requests or *intents*. Each request represents a bandwidth demand of a network-based service or application having a unique daily traffic pattern. We assume multiple requests per each node pair. All of the requests are active in the network

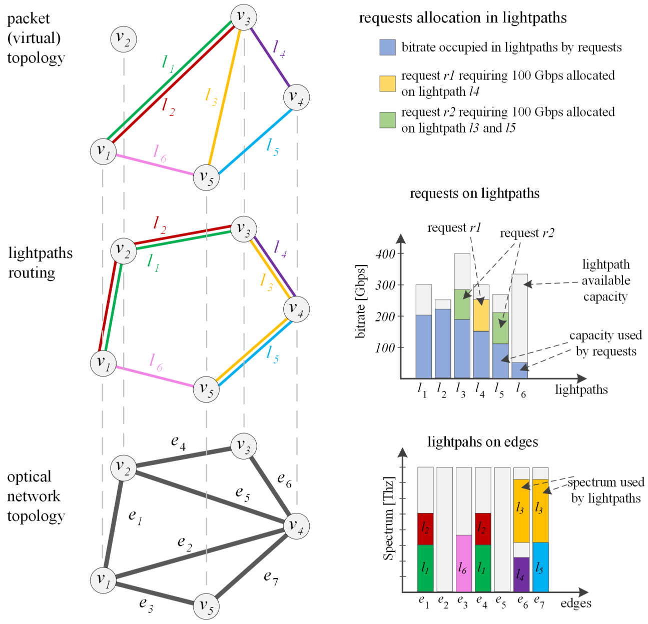

Fig. 1: Overview of the network model and traffic grooming as in [14].

during the entire duration of the simulation, but their bitrate changes. More details will be provided in Section III.

In this work, we aim to simulate and evaluate the network operation under various types of traffic. To this end, we use our recent multilayer RSA algorithm proposed in [14]. The base version, multilayer (MLTL), assumes a separate lightpath for each connection request to accommodate its bitrate changes throughout the day. In case of a bitrate increase over the lighpath capacity, a new lighpath is established for this connection. The lightpaths are established in the optical network using a heuristic that sorts the $k = 10$ shortest paths according to the lowest-possible slot assignment of a potential channel. According to our previous experiments, such an approach allows provisioning up to 20% more traffic than the conventional sorting of candidate paths by their length. Moreover, it spreads the load in the network more evenly to avoid congestion. For spectrum assignment we use the well-known First Fit heuristic, recently proven as universal [15].

Our algorithm modification, multilayer with grooming (MLTL_G), adds traffic grooming [16] and routing in the IP layer. In particular, for any initially allocated or reallocated request, if there is a direct lightpath from its source to its destination with enough spare bandwidth, the request is added into it. In turn, multiple requests can share resources resulting in considerable savings. Moreover, $k = 3$ shortest paths in the top layer sorted by the number of hops are also considered. According to our previous experiments, this number of candidate paths balances virtual path length and resource utilization.

The algorithms make their allocation and grooming decisions using the expected bitrate within the upcoming period with a granularity of 5 minutes. As in [14], we create traffic forecasts for each connection request using its month-long history. Our model, based on previous work [17], makes the predictions using a linear regression model built around the relationship between the current traffic and its samples in significant past points in time – a day and a week before.

III. Experimental setup

In this Section, we report the setup of our experiments. We perform computer simulations to evaluate the network performance thoroughly using the algorithm described above. In our experiments, we consider two large topologies with diverse characteristics, illustrated in Fig. 2 and available in the SNDLib library [18]. We assume the Ciena Wavelogic 5 Extreme transceiver with its specifications as provided in [19].

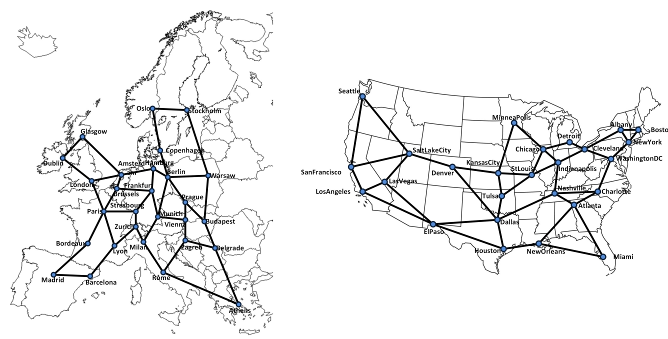

Fig. 2: Considered network topologies: Euro28 with 28 nodes and 82 links (left) and US26 with 26 nodes and 84 links (right).

For a thorough evaluation, we generate multiple *semi-synthetic* datasets using the Traffic Weaver package [20]. We select seven diverse traffic patterns provided in the Sandvine report [7] plotted in Fig. 3. To test the network performance under a traffic pattern, we generate five sets of requests sharing the traffic pattern and differing bitrate for each topology. In other words, each dataset contains 1000 requests of the same traffic pattern, having a bitrate scaled to the 50–100 Gbps range with a uniform distribution. The network operation is simulated for various traffic loads, which is increased by increasing the number of active connection requests. The results contain values averaged over simulations using requests of the same type.

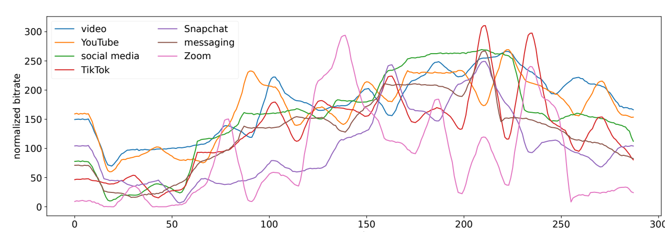

Fig. 3: Considered traffic patterns from the Sandvine report [7] prepared using the Traffic Weaver [20].

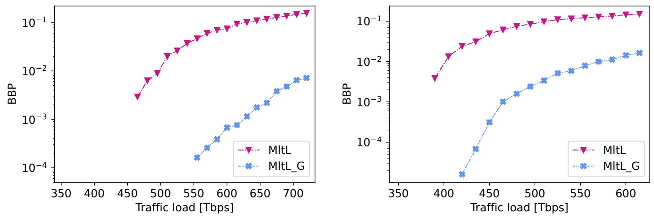

Fig. 4: BBP for request type *messaging*. US26 topology (left) and Euro28 topology (right).

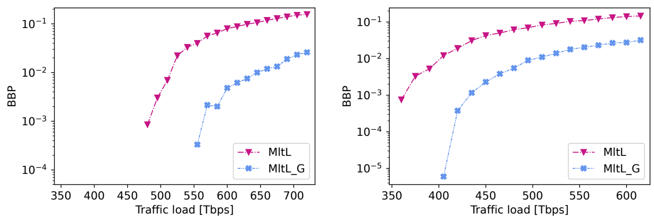

Fig. 5: BBP for request type *social media*. US26 topology (left) and Euro28 topology (right).

IV. Results

In this Section, we discuss the results we obtained. First, let us investigate the advantages coming from using traffic grooming and how they differ between topologies and traffic patterns. To this end, we consider the Bandwidth Blocking Probability (BBP) metric, describing the ratio of blocked to total bandwidth. The results from this part are plotted in Fig. 4 – Fig. 10. As expected, employing traffic grooming results in vastly reduced BBP. However, the advantages differ between the test cases.

The first overall trend visible there is the difference between the appearance of the first blocking events for the MltL_G algorithm compared to the baseline MltL. It comes at a much higher traffic load in the case of the US26 topology compared to Euro28. In turn, the advantages of employing traffic grooming are more profound in the more spread-out topology, regardless of the traffic type. Furthermore, under traffic loads, which results in some blocking in both algorithms, the differences between them are once again more significant in the case of US26. As revealed in our previous study [21] comparing the impact of node restrictions in those two networks, Euro28 is more dense, and its crucial nodes for connection provisioning lie close to each other and get congested fast. Thus, it is essential to use any mechanisms that utilize the available resources in the best possible way.

Let us now focus on the differences between traffic types. As illustrated in Fig. 3, some patterns, including TikTok or Zoom, contain large spikes within the day's span. Their influence is reflected in the results. In particular, the difference between BBP achieved with and without traffic grooming appears to be the smallest compared to the remaining tested patterns. We may suspect that the enormous changes in bitrate result in

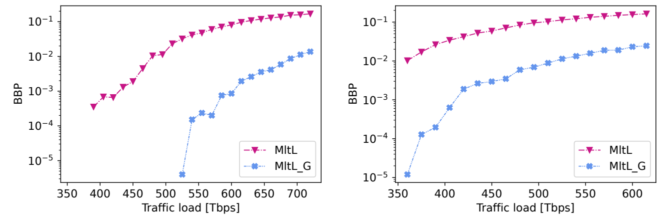

Fig. 6: BBP for request type *video*. US26 topology (left) and Euro28 topology (right).

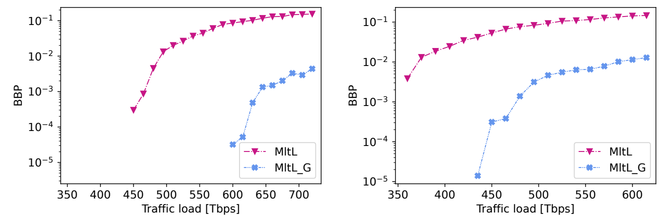

Fig. 7: BBP for request type *YouTube*. US26 topology (left) and Euro28 topology (right).

frequent reallocations and, thus, many lightpath configuration changes that may cause fragmentation. The additional connection requests that all momentarily increase in bitrate create the need for additional channels to be created, which, under higher loads, might be impossible due to the lack of available resources.

For a better illustration of the network performance with various traffic types, we now present the results of a second metric – accepted traffic assuming BBP of 1%. We calculated it as a linear approximation of the traffic load between the first BBP over 1% and the last BBP under 1%. Contrary to

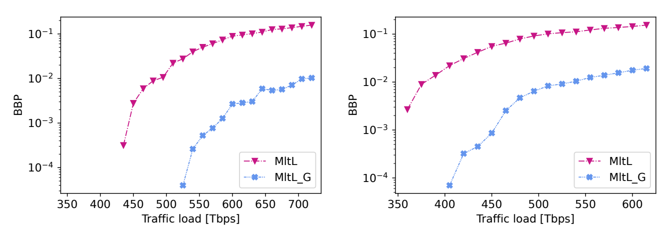

Fig. 8: BBP for request type *Zoom*. US26 topology (left) and Euro28 topology (right).

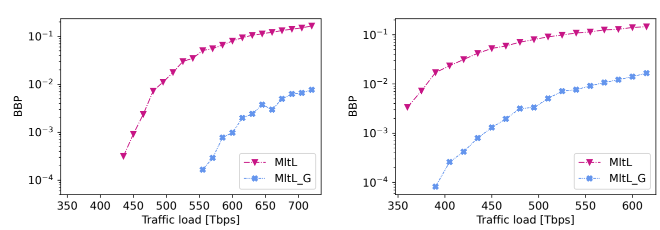

Fig. 9: BBP for request type *Snapchat*. US26 topology (left) and Euro28 topology (right).

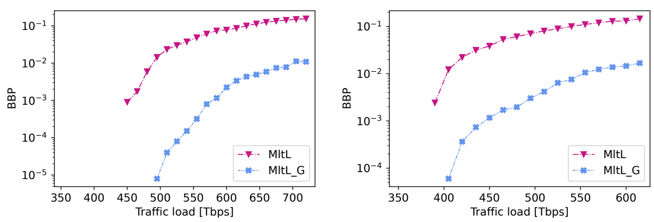

Fig. 10: BBP for request type *TikTok*. US26 topology (left) and Euro28 topology (right).

TABLE I: Accepted traffic [Tbps] assuming 1% BBP – average over 180 simulations per traffic type; Euro28 topology.

traffic type	**MltL**	**MltL_G**
messaging	40.35	57.15
social media	40.35	49.95
video	37.65	52.05
YouTube	37.65	59.55
Zoom	39.45	54.45
Snapchat	38.55	57.15
TikTok	40.35	55.05

the previously discussed measure, accepted traffic should be maximized. The results are presented in Tab. I and Tab. II. The trends align with our discussion above, numerically presenting the great advantages of utilizing traffic grooming for diverse types of time-varying connection requests; the amount of traffic accepted in the network drastically increases after employing traffic grooming. The differences in both topologies are the smallest for the least fluctuating social media traffic, and the advantages increase for more time-variable traffic types.

Finally, let us discuss the advantages of using the knowledge coming from traffic prediction. To this end, we calculated the Bandwidth Blocking in Established Lightpahts (BBEL) expressed in Gbps. This measure describes the portion of bitrate that was blocked due to the lack of prior knowledge about the upcoming traffic and making incorrect assumptions about it (in particular, prediction errors in case of prediction-guided methods). Suppose a request needs reallocation and is expected to have a bitrate of 42 Gbps in the forthcoming period. There is a fitting lightpath with 45 Gpbs free bandwidth. In such

TABLE II: Accepted traffic [Tbps] assuming 1% BBP – average over 180 simulations per traffic type; US26 topology.

traffic type	**MltL**	**MltL_G**
messaging	49.65	75.75
social media	51.45	64.65
video	48.15	70.05
YouTube	49.05	76.95
Zoom	48.15	72.45
Snapchat	49.05	74.25
TikTok	49.65	72.45

TABLE III: BBEL [Gbps] – average over 180 simulations per traffic type. MltL_G algorithm, Euro28 topology.

traffic type	**conventional**	**with prediction**
messaging	4744.54	16.25
social media	3934.36	27.71
video	4881.10	25.15
YouTube	6046.16	13.67
Zoom	20769.72	13.25
Snapchat	10510.41	13.37
TikTok	19581.54	11.94

a case, the algorithm performs traffic grooming and adds the request to the channel. However, suppose that the actual bitrate of this request in the next period has grown to 50 Gbps. In this case, the "additional" 5 Gbps is blocked due to the erroneous assumptions (e.g., prediction or any other future bandwidth assumption policy).

In Tab. III and Tab. IV, we compare the performance of the MltL_G algorithm with and without the ML-based traffic prediction. The latter is denoted in tables as "conventional" and assumes that the traffic in the upcoming 5 minutes will be the same as in the current moment. Contrarily, the former case uses the predicted bitrate for the algorithmic decisions. Interestingly, the differences between both approaches are quite enormous, several orders of magnitude. This proves the effectiveness of using prior knowledge about the upcoming traffic for better provisioning. This is especially important as both approaches resulted in the BBP and accepted traffic on a comparable level, with a slight advantage towards the one using predictions.

Between traffic types, there is an enormous difference in the amount of blocked bandwidth between the highly- and moderately fluctuating patterns. It is easily noticeable that for traffic not drastically changing throughout the day, like messaging or social media, the BBEL is around 4000 Gpbs. However, it drastically increases by two orders of magnitude with highly variable patterns, like Zoom or TikTok. Remarkably, those differences almost vanish after employing simple traffic prediction models. Thus, similar to traffic grooming, forecasting greatly benefits the performance of multilayer networks with time-varying traffic. Once again, the gains differ between specific types of connection requests.

Additionally, the knowledge from traffic prediction can be utilized for advance reservation (AR). In the last set of results, we discuss how much this process influences the network operation. To this end, we once again consider the MltL_G algorithm with traffic prediction and its modification proposed in [14] and denoted here as MltL_G_AR. This version checks the current bitrate trend of each request and, if it is increasing, considers its 15-minute maximum for decision-making to prevent frequent reallocations. In our testing, both versions resulted in the BBP and accepted traffic on a similar level with a slight advantage towards the regular MltL_G,

TABLE IV: BBEL [Gbps] – average over 180 simulations per traffic type. MltL_G algorithm, US26 topology.

traffic type	conventional	with prediction
messaging	4562.36	35.98
social media	3396.86	50.67
video	3657.20	24.14
YouTube	4584.80	27.42
Zoom	15441.89	14.44
Snapchat	9440.39	22.89
TikTok	16255.93	20.82

TABLE V: BBEL [Gbps] – average over 180 simulations per traffic type. Comparison of the MltL_G and MltL_G_AR algorithms, Euro28 topology.

traffic type	MltL_G	MltL_G_AR
messaging	16.25	14.54
social media	27.71	25.05
video	25.15	20.42
YouTube	13.67	10.78
Zoom	13.25	10.54
Snapchat	13.37	10.73
TikTok	11.94	9.22

and in Tab. V and Tab. VI, we report their BBEL. It is clear how the AR results in a lower BBEL in all types of traffic. Differences are, however, less spectacular than in the previous sets of results. Therefore, the decision to utilize AR should be taken individually for each connection request. Reserving the resources in advance for some requests can potentially cause the blocking of others. On the other hand, it mitigates the effects of traffic prediction errors to a greater extent and, as shown in [14], vastly decreases reallocation frequency.

V. Conclusions

In this paper, we investigated the impact of traffic type on the performance of multilayer networks with time-varying traffic. We conducted a broad experimental evaluation on two representative topologies under multiple metrics. The results revealed how the network operation changes with various traffic patterns. The simulations explored the advantages from using traffic grooming and different uses of traffic prediction and how they change with changing traffic.

TABLE VI: BBEL [Gbps] – average over 180 simulations per traffic type. Comparison of the MltL_G and MltL_G_AR algorithms, US26 topology.

traffic type	MltL_G	MltL_G_AR
messaging	35.98	32.06
social media	50.67	46.22
video	24.14	21.45
YouTube	27.42	21.07
Zoom	14.44	13.23
Snapchat	22.89	19.82
TikTok	20.82	18.96

The study's results are a great resource for the design of new application-aware network optimization algorithms which we plan to develop in the future.

Acknowledgment

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