Joint Optimization of Packet and Optical layers of a Core Network Using SDN Controller, CD ROADMs and machine-learning-based traffic prediction

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Abstract— **We show significant cost savings and improved robustness by combining machine learning with joint global optimization of IP and optical layers in a core network through the use of SDN, CD ROADMs and DFCC devices.**

Index Terms — **Machine Learning; Traffic Matrix Prediction; Multi-Layer Optimization; SDN.**

I. INTRODUCTION

The traffic management of a core IP/Optical backbone of a large Internet Service Provider (ISP) must deal with dynamic traffic changes under various network conditions including scheduled and unscheduled outages, and make efficient use of network resources (IP + Optical) while also satisfying the loss and latency requirements of each class of traffic type it carries [1, 2]. The IP layer of the network consists of IP links connected among IP devices such as router ports or white-box switch ports. The IP links are routed over a path in the optical layer using ROADMs, transponders at endpoints, and optical signal regenerators along the path when it is longer than the system optical reach. We use machine learning [3-5] for accurate short-term and long-term prediction of all elements of the traffic matrix, combine that with joint global optimization of IP and optical layers [5,6] using Colorless/Directionless (CD) ROADMs [5,7] and Multi-Layer SDN (Software Defined Network) controller [2, 8] for implementation. This results in significant cost savings, flexible new services to meet dynamic capacity needs with better accuracy, and increased robustness by being able to proactively adapt to new traffic patterns and network conditions.

II. FRAMEWORK FOR CLOSED LOOP OPTIMIZATION USING MACHINE LEARNING

Figure 1 depicts the framework for self-optimizing an IP/Optical network in a closed loop manner where future traffic prediction from machine learning, real-time network and traffic measurements, and knowledge based feedback on traffic changes and failures will collectively drive a joint global optimization engine for both the packet and optical layers.
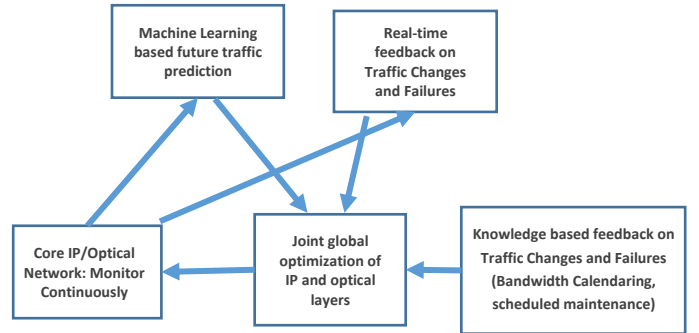

Fig. 1. Closed Loop Optimization with Machine Learning and other Feedbacks.

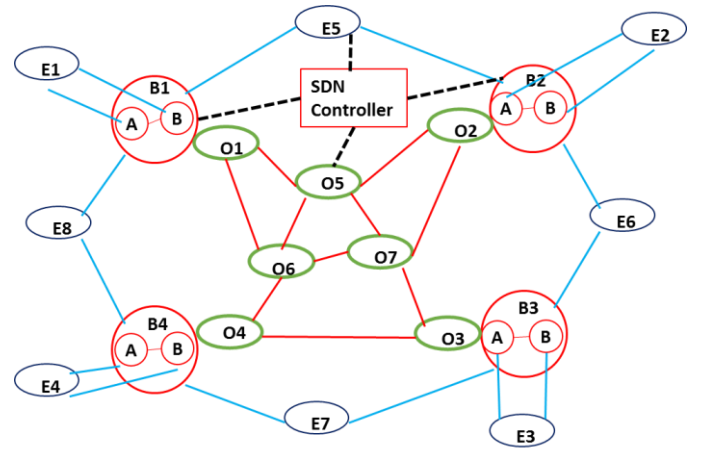## III. ROUTING OF TRAFFIC OVER PACKET/OPTICAL NETWORK

Fig. 2. Example IP/Optical Network with Backbone (B), Edge (E) and optical (O) locations.

Figure 2 illustrates an example of an integrated IP/Optical network and its interaction with the SDN controller. Ei represents the IP edge routers, Bi represents IP core locations and Oi represents optical nodes (ROADMs). A subset of the optical nodes are collocated with IP core locations. All traffic originates/terminates at the edge routers and each such router is connected to at least two core routers using physically diverse paths.

Figure 3 explains various levels of routing in the network. The IP links are routed over the ROADM layer and the MPLS

TE (Traffic Engineering) tunnels carrying end-to-end traffic are routed over the IP layer.
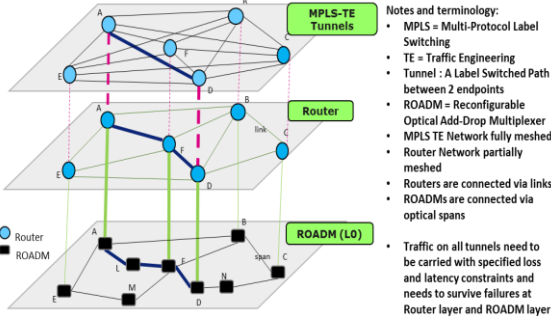

Fig. 3. Various Levels of Routing.

IV. FLEXIBILITY OF RESOURCE MANAGEMENT WITH CD ROADMS AND DIGITAL FIBER CROSS CONNECT (DFCC) DEVICES

Figure 4 shows an end-to-end routing of an IP link over the optical layer. R1 and R2 represent router ports in two different geographical locations. T1 and T2 are transponders used in the two locations for electrical-to-optical and optical-to-electrical signal conversions. The connected combination of a router port and transponder in the same location is called a Tail and we have two tails in this illustration: Tail1 and Tail2. There are many ROADMs in the optical network and electronic regenerators (e.g., RE1 as shown in the picture) needed to boost signal strength if the route-miles from ROADM1 to ROADM4 is beyond the system optical reach. We also use a Dynamic Fiber Cross-connect (DFCC) device [9] to dynamically connect two components of the Tail.

Traditionally, if any component along the path of the IP link fails (or there is a fiber-cut), the entire IP link fails and no non-failed component can be reused. However, with an SDN controller managing both the packet and the CD ROADM networks [8], the three components, namely Tail1, Tail2 and RE1 are disaggregated and can be reused by the controller. Furthermore, the DFCC device also disaggregates the two components of the Tail and if one of its components fails, the non-failed component can be reused and combined with another component of the opposite type to form a new Tail. The real-time SDN controller can leverage this resource disaggregation capability to optimize and proactively overcome traffic fluctuations and network failures.

V. MACHINE LEARNING-BASED FUTURE TRAFFIC PREDICTION

If there are N traffic endpoints and K QoS classes then there are $T = KN(N-1)$ elements in the traffic matrix. As an example, if $K = 2$ and $N = 50$ then $T = 4900$. We assume that each element of the traffic matrix is routed over the packet network as a TE tunnel. Typically, the TE tunnel traffic at a large ISP network is characterized by complex, nonlinear oscillations and seasonal periodicities at different time scales, reflecting customer usage of the network. The traffic on the highest-activity tunnels contains a strong daily oscillation, a less prominent weekly oscillation along with occasional sharp jumps that correspond to the network dynamically shifting traffic between tunnels following an IP topology change.
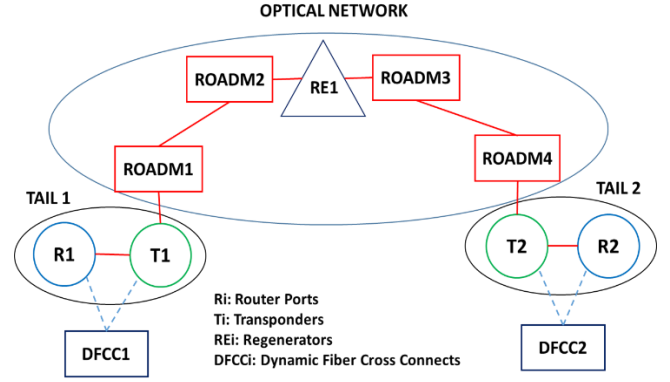

Fig. 4. End-to-end Routing of IP Link over Optical Layer.

We predict TE tunnel traffic by applying a nonlinear, autoregressive-like time series model based on Gaussian process regression (GPR), a Bayesian regression technique where the number of parameters estimated grows with the amount of data. Our approach models the relationship between the past and present values of the traffic as a realization of a Gaussian process, and applies GPR to lagged sections of the data to estimate the relationship. See [5] for more details. We use data collected from a large ISP network over a eight-month period, with the data from the first seven months used for training models of this type, and the data for the next one month for testing the model's performance, where a_T is the desired forecast horizon.
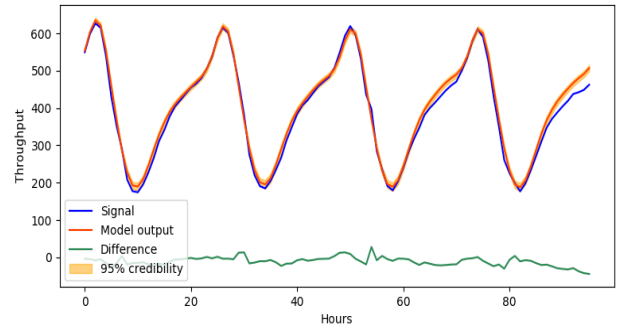

Fig. 7. The total traffic over all tunnels (blue) and a 4-day forecast formed by multiple models (red) trained over the previous three months with $a_T \in \{1, 2, ... 96\}$. The relative MAE (Median Absolute Error) over the whole test period is 1.61% and the relative MAE over the peak periods is 1.12%. Generic BW units are used.

VI. USING MACHINE LEARNING AND OTHER FEEDBACK TO OPTIMIZE AT VARIOUS TIME SCALES

SDN optimization and Machine learning (ML) techniques can be applied at many different time scales.

Fast Reroute (FRR) in the Sub-Second Time Scale: With ML- based timely traffic prediction we can periodically re-adjust and optimize FRR bypass paths.

Layer 3 Tunnel Changes in the Seconds-to-minutes Time Scale: Real-time machine learning can make the changes proactive causing less disruption to traffic.

Minutes-to-hours Time Scale: In addition to being able to reroute TE tunnels over fixed IP links, we can also use the flexibility of CD ROADMs and DFCC to create new IP links,

delete or reroute an existing IP link based on changing network and traffic conditions (uses ML-based predictions).

Days, weeks and months Time Scale: We predict resources that need to be ordered based on simulating many failure scenarios in an integrated multi-layer fashion based on ML-based future traffic predictions over days and weeks.

Optimization Methodology: We developed efficient heuristics to optimize over many different failure scenarios and joint global optimization of optical and IP layers using the flexibility of CD ROADMs and DFCC. The heuristics provide a close to optimal solution while reducing execution times by orders of magnitude. More details in [5].

VII. COMPARISON OF TRADITIONAL DESIGN AND OPERATION OF IP/OPTICAL NETWORKS WITH THAT BASED ON MACHINE LEARNING AND JOINT MULTILAYER OPTIMIZATION

Improved Efficiency: Table I shows improved efficiency and cost reduction with machine learning based traffic prediction combined with joint multilayer optimization at a large ISP network with a large number of MPLS-TE tunnels. All numbers shown are generic normalized values and are only to be used to compare among the different scenarios. Analysis is at the one month time scale to determine the minimal number of resources needed to satisfy all potential failure and traffic loss scenarios over that period of time. For the purpose of this analysis we assume that we have to optimize over three types of resources, Transponders, IP ports and Regens (all 100 GE). The cost is given in units of Transponders and for the purpose of illustration, it is assumed that the costs of IP ports and Regens are 2.5 and 1.5 times that of a Transponder. We consider five cases:

1. No Machine Learning, IP Layer Optimization Only, and fixed IP to Optical mapping: Requires extra capacity to account for traffic uncertainties.
2. Addition of Machine Learning: In this scenario, we have more precise knowledge of time-of-day and day-of-week traffic variation allowing for a tighter network design.
3. Addition of Joint Multilayer Optimization with a Fixed IP Layer Topology: We use the same set of IP links under all conditions as in the above two scenarios but the capacity of an IP link can be readjusted. Under a given failure scenario if a subset of components fail then the remaining non-failed components can be reused to enhance the capacity of an existing IP link.
4. Addition of Dynamically Changing IP Layer Topology as traffic changes: Here for each failure scenario and traffic surge scenario, we rearrange the number of IP links and their routing over the optical network in order to optimally use the Tail and Regen resources. We use Machine learning to anticipate short-term traffic changes and change IP layer topology proactively.
5. Addition of DFCC: Furthermore, we typically have two Routers in every office and if one fails then we can use DFCC to create a new Tail using a port of the other Router and re-using the transponder. Even without a complete Router failure, DFCC can be used to connect a Transponder to a different Router port in the same office if needed for more efficient Routing.

Table I. Normalized View of Efficiency Gains with Machine Learning for Traffic Prediction Combined with Multi-Layer Optimization

Scenario	100 GE Transponders	100 GE IP Ports	100 GE Regens	Normalized Cost
1. No Machine Learning, IP Layer Optimization Only, fixed IP to Optical mapping	1,000	1000	100	3650
2. Addition of Machine Learning at long time-scale	910	910	90	3320 (-9%)
3. Addition of Joint Multilayer Optimization with a Fixed IP Layer Topology	815	815	80	2972 (-19%)
4. Addition of Dynamically Changing IP Layer Topology as traffic changes (short-term ML-based forecast)	715	715	115	2675 (-27%)
5. Addition of DFCC	620	680	115	2492 (-32%)

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