# An Effective Strategy for Link Upgrade from C to C+L Band in Elastic Optical Backbone Networks

Ramanuja Kalkunte
*University of California, Davis*, USA
rkalkunte@ucdavis.edu

Forough Shirin Abkenar
*University of California, Davis*, USA
fshirina@ucdavis.edu

Rana Kumar Jana
*Indraprastha Institute of Information Technology, Delhi*, India
ranaj@iiitd.ac.in

Davide Aureli
*INPS*
Rome, Italy
davide.aureli@inps.it

Sifat Ferdousi
*University of California, Davis*, USA
sferdousi@ucdavis.edu

Anand Srivastava
*Indraprastha Institute of Information Technology, Delhi*, India
anand@iiitd.ac.in

Abhijit Mitra
*Indraprastha Institute of Information Technology, Delhi*, India
abhijit@iiitd.ac.in

Massimo Tornatore
*Politecnico di Milano*, Italy
massimo.tornatore@polimi.it

Biswanath Mukherjee
*University of California, Davis*, USA
bmukherjee@ucdavis.edu

***Abstract*—Multi-band transmission is a promising solution for capacity enhancement in optical networks. We propose a novel strategy, named C to C+L Upgrade (CLU), to gradually upgrade links from C to C+L bands. We develop a Recurrent Neural Network (RNN)-based model to efficiently predict links for upgrade, based on network state and resource utilization, to reduce blocking and upgrade cost. Our results show that CLU outperforms baseline strategies (which do not employ predictive decisions) by upgrading fewer links at appropriate times.**

***Index Terms*—C+L, recurrent neural network, upgrade, spectrum utilization, blocking probability.**

## I. Introduction

With the growth of bandwidth-hungry services in the 5G/6G era, it is crucial for network operators to allocate sufficient resources in optical backbone networks [1]. With the emergence of Elastic Optical Networks (EONs), spectral efficiency of the available C-band spectrum in single-mode fibers (SMFs) can be enhanced; however, C-band capacity is limited to approx. 5 THz [2]. Hence, Multi-band (MB) technology is emerging as a promising solution for the capacity-crunch issue by utilizing additional bands in SMFs - especially the L band which exhibits only a negligible increase in attenuation compared to C band while providing an additional 5 THz bandwidth [3].

Expansion to MB requires network operators to upgrade network links, but this operation incurs significant Capital Expenditure (CapEx) and Operational Expenditure (OpEx). Prior works have proposed link-upgrade strategies for MB expansion to sustain traffic growth, while considering upgrade costs. For example, authors in [4] showed the significance of proper link selection by introducing a framework which accounts for geographical dependence of fiber-capacity upgrades. Authors in [5] proposed a planning strategy for determining the set of fibers for upgrade which could lower upgrade costs. Similarly, Ref. [6] proposed a multi-period batch-upgrade model from C to C+L using resource utilization as a metric to select a group of links for upgrade. Although these studies offer various upgrade strategies, they consider only current resource utilization in the network to assess the need for upgrades and do not consider monitoring-based prediction mechanism for timely and effective link selection for upgrade.

Emphasizing the significance of timely upgrades, we note that, while early upgrades can mitigate occurrence of blocked connections, i.e., reduce Blocking Probability (BP) in the network, delaying upgrades can yield cost benefits stemming from equipment depreciation. Therefore, it is important for network operators to carefully choose times for upgrade to reduce blocking and reduce upgrade cost in the network. Since dynamics of blocking and cost are time-dependent, a Machine Learning (ML)-based model capable of continuously monitoring changes in the network state would be ideal to predict suitable links for upgrade at appropriate times. The Long Short-Term Memory (LSTM) variant of Recurrent Neural Network (RNN), thanks to its capability of storing/retrieving information over both short- and long-time periods and of capturing non-linear patterns, make it a strong candidate for tracking changes over time [7]. In this paper, we propose a novel link-upgrade strategy, named C to C+L Upgrade (CLU), and develop an LSTM-based model that leverages information such as resource utilization, fragmentation, etc., over time to efficiently predict the links that will more likely need an upgrade. Our objective is to reduce BP in the network, while increasing cost savings by adhering to a given upgrade budget.

## II. System Model

We consider an elastic backbone optical network topology, $G(V, E)$, comprising $|V|$ nodes and $|E|$ links, where $V$ represents the set of nodes and $E$ represents the set of links. In our study, we consider C and L bands, with each band comprising 133 channels (considering 37.5 GHz frequency spacing [2]), and the network initially operates only in C band. Incoming traffic is quasi-static where requests enter and remain in the network (which is a common scenario for telecom network operators catering to clients requesting high-bandwidth pipes). Source-destination pairs are generated using a gravity model where traffic generation probability of each node is based on its population density. The set of requests is denoted by $R$; each request $i \in R$ is represented by a tuple $(S_i, D_i, F_i)$ where $S$, $D$, and $F$ are source, destination, and required Frequency

Slots (FSs), respectively. We define an upgrade budget $\hat{J}$, which is decremented after each link upgrade in the network.

In this work, given an EON operating in C band, a set of requests, and an upgrade budget, we employ a ML model to effectively select *which links* to upgrade at *what time*, such that BP and upgrade costs are reduced.

### A. Upgrade Cost Model

Authors in [8] show that the cost of upgrading a link is influenced by two key factors: number of Erbium-Doped Fiber Amplifiers (EDFAs) and type of switches employed on links. When upgrading from C to C+L bands, the cost significantly rises due to the necessity of installing separate EDFAs to support L-band transmission [5], [9]. On the other hand, to support both C- and L-band transmission, wavelength-selective, band-switchable, multi-band optical cross-connect switches (MB-OXCs) must be installed at all nodes, eliminating the need for separate switches for L band.

We denote $d_e$ and $d^*$ as the length of link $e$ and the maximum amplifier span for C and L bands, respectively. Taking into account one pre-amplifier and one post-amplifier on each link, the total number of L-band EDFAs required for upgrade on link $e$ is given by $(\lceil d_e/d^* \rceil + 2)$ [9]. We denote $J_{EDFA}$ as the cost of each EDFA on link $e$ and $J_{WSS}$ as the cost of a Wavelength-Selective Switch (WSS) at each end of link $e$. Considering an equipment depreciation factor of $\delta \in [0, 1]$ for EDFA over a span of $y$ years [6] (impact of cost depreciation for WSS is considered negligible due to its lower cost), the cost of upgrade for link $e$ is given by:

$$J_e = \left( \left\lceil \frac{d_e}{d^*} \right\rceil + 2 \right) \cdot J_{EDFA} \cdot (1 - \delta)^y + 2 \cdot J_{WSS} \qquad (1)$$

Eq. (1) implies that the upgrade cost exponentially decreases w.r.t. the upgrade time so that delaying an upgrade can lead to significant cost savings. However, it can increase BP; hence, determining the appropriate upgrade time is crucial.

### B. Cumulative Blocking Probability per Link

Total BP in a network depends on spectrum utilization (SU) and fragmentation ratio (FR) of the links. SU is defined as the ratio of FSs occupied on a link to the total bandwidth of the link [10]. Considering $R_e(t)$ as the set of requests provisioned over link $e$ at time $t$ and $B_e$ as the total capacity of link $e$, SU (denoted by $\mu$) is given as:

$$\mu_e(t) = \frac{\sum_{i \in R_e(t)} F_i}{B_e} \qquad (2)$$

On the other hand, FR of a link depends on sets of available continuous FSs, known as Slot Blocks (SBs). Considering $G_e(t)$ as the set of available SBs on link $e$ at time $t$ and $H_j$ as the size of the $j$-th available SB on link $e$, FR (denoted by $\eta$) is expressed as [11]:

$$\eta_e(t) = 1 - \frac{\max_{j \in G_e(t)} H_j}{\sum_{j \in G_e(t)} H_j} \qquad (3)$$

To alleviate total BP in the network, links over which more requests are likely to be blocked need to be upgraded sooner.

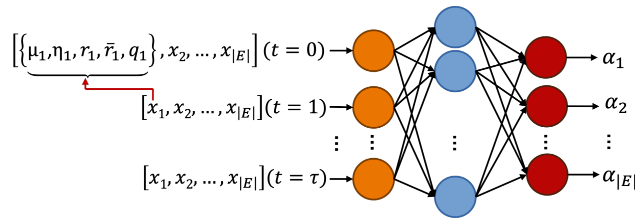


Fig. 1. Proposed RNN-based model incorporating link features.

In this regard, we define *Cumulative Blocking Probability per Link* (CBPL) as the ratio of the number of blocked requests to the total number of requests over a link. Since requests are provisioned using a Routing and Spectrum Allocation (RSA) strategy, which influences the SU and FR of a link, exact mathematical representation of CBPL is challenging. Hence, we develop a LSTM (variant of RNN)-based model to predict CBPL of the links as a function of SU and FR; details of the model are described in Section III-A.

## III. CLU: C to C+L Upgrade Strategy

During MB upgrades, it is crucial to reduce both blocking and upgrade cost in the network. We propose a novel upgrade strategy, namely CLU, to reduce BP and avoid untimely upgrades leading to high cost. To achieve this goal, we design an algorithm to identify the most suitable link(s), based on CBPL threshold (i.e., the maximum allowable CBPL as set by the operator) and budget constraint, for upgrade at appropriate times. The upgrade budget ($\hat{J}$) is derived by calculating the cost of upgrading *all* links in the network at the beginning, which results in the maximum cost as it does not consider any link selection criteria and equipment cost depreciation.

### A. RNN-Based CBPL Estimation Model

To efficiently predict CBPL of the links, we develop an RNN-based model employing a LSTM architecture. In Fig. 1, we show the structure of the proposed model, which comprises an input layer, a hidden layer, and an output layer. Each link $e \in E$ has a set of five features, indicated by $x_e(t) = \{\mu_e(t), \eta_e(t), r_e(t), \bar{r}_e(t), q_e(t)\}$, where $\mu_e(t)$, $\eta_e(t)$, $r_e(t)$, $\bar{r}_e(t)$, and $q_e(t)$ represent SU, FR, total number of served requests, total number of blocked requests, and number of remaining FSs on link $e$, respectively. The input layer is composed of the features of all links for $\tau$ time steps, e.g., in Fig. 1, we show the features of link 1 ($x_1$) at time $t = 0$. On the other hand, the output layer consists of $|E|$ nodes, each corresponding to CBPL (denoted by $\alpha_e$) of a link $e \in E$; the model observes previous time steps to predict CBPL at $t + 1$.

### B. Algorithm

Algorithm 1 summarizes the steps of CLU which takes network topology, set of requests ($R$), CBPL threshold ($\tilde{\alpha}$), and upgrade budget ($\hat{J}$) as inputs. Total BP ($\mathrm{A}_{Total}$) is initially set to 0. Then, it employs the k-Shortest Path algorithm to identify candidate paths for the incoming requests and allocates FSs to each request using the First-Fit (FF) mechanism. Requests unable to secure FSs are classified as blocked. Following this,

**Algorithm 1** CLU Algorithm

**Input:** $G(V, E)$, $R$, $\tilde{\alpha}$, $\hat{J}$;
**Output:** Total upgrade cost, upgraded links, $\mathrm{A}_{Total}$;
**Initialize:** $\mathrm{A}_{Total} = 0$;
**for** each time $t$ **do**
  **for** all incoming requests **do**
    Perform corresponding RSA;
  Update $\mathrm{A}_{Total}$ accordingly;
  **for each** $e \in E$ **do**
    Estimate $\alpha_e(t + 1)$ using the RNN-based model;
    Calculate $J_e$ using Eq. (1);
  $E' \leftarrow$ Sorted links in descending order of $\alpha_e(t + 1)$;
  **for each** $e \in E'$ **do**
    **if** $\alpha_e(t + 1) \geq \tilde{\alpha}$ && $J_e \leq \hat{J}$ **then**
      Upgrade $e$ and remove it from $E$;
      $\hat{J} -= J_e$;

$\mathrm{A}_{Total}$ is updated based on the number of blocked requests and the number of served requests in the network. In the next step, CLU estimates the CBPL of all un-upgraded links for the next time instance ($t$+1) using the proposed RNN-based model and sorts them in descending order of CBPL. In addition, upgrade cost of each link at time $t$ is calculated using Eq. (1). Finally, it chooses the links that satisfy both $\tilde{\alpha}$ and $\hat{J}$ for upgrade, removes them from the set of candidate links, and updates $\hat{J}$.

## IV. Numerical Evaluation

### *A. Modeling and Simulation Setup*

An event-driven, custom-built, Python simulator is used to model (i.e., emulate) an upgrade environment from C to C+L band. Simulations are performed on the Indian RailTel network (see Fig. 2) consisting of 19 nodes and 28 bi-directional links [2]. L-band amplifiers are deployed at regular intervals of 80 km. We repeat and average the simulations for 15 different seeds, each with about 1800 quasi-static demands. We assume equipment cost to upgrade one link from C to C+L as $J_{EDFA} = 1$ unit, with yearly depreciation of $\delta$ = 5%, and $J_{WSS} = 0.5$ unit. Using Eq. (1), we derive $\hat{J}$ = 512 units. To train/test the CBPL model, the dataset is obtained through simulating numerous seeds and extracting necessary link features. The data is split in chunks of $\tau$ time steps (for our simulation, $\tau$ is set to 10).

### *B. Preliminary Evaluation of Baseline Approaches*

To demonstrate the efficiency of CLU, we consider two intuitive baseline approaches: Basic Spectrum Utilization (BSU) and Cost-aware Spectrum Utilization (CSU). In BSU, links that exceed a predefined SU threshold ($\tilde{\mu}$) are candidates for upgrade. Since it does not consider budget constraint, we introduce, as an extension of BSU, a cost-aware approach, CSU, which not only checks $\tilde{\mu}$, but also checks if the candidate links can accommodate one or more requests (over a single hop) so as to delay upgrades and reduce cost. We model CSU to postpone upgrades for up to $n$ iterations (e.g., if $n = 3$, we check upto three times if a link can accommodate one more request and hence delay the upgrade).

Since performance of CSU varies over $n$, we evaluate its performance w.r.t. $n$. As shown in Fig. 3, we compare BP of

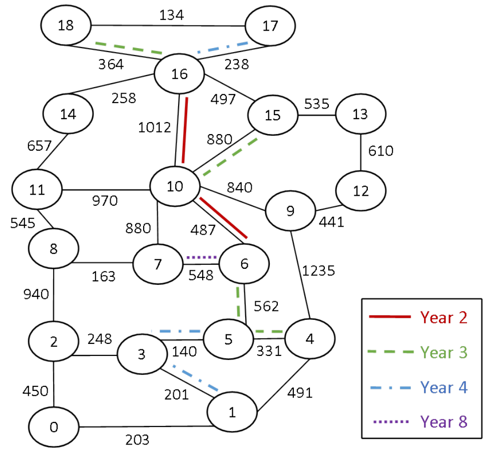


Fig. 2. Indian RailTel network with link lengths in km. Gradual link upgrades by CLU (for $\tilde{\alpha}$ = 0.05) are shown by solid and dashed lines.

CSU for different values of $n$ with BSU. Since BSU relies only on $\tilde{\mu}$ to initiate an upgrade and does not wait to accommodate additional requests, BSU exhibits the lowest BP compared to CSU. Results also show that, with every increment of $n$, BP continues to rise in CSU as postponing the upgrade leads to higher BP. However, it also leads to lower cost as shown in Fig. 4 which compares the total upgrade cost of CSU for different values of $n$ with BSU. Here, the cost of BSU is almost comparable to CSU when $n = 1$ and $n = 3$ for $\tilde{\mu} = 0.4$. However, when $n = 8$, the upgrade cost is lower for all values of $\tilde{\mu}$. Since CSU aims to delay upgrade, higher values of $n$ will lead to lower cost. Considering both blocking and cost evaluation, CSU ($n = 3$) is selected for comparison with CLU as it gives reasonable trade-off between BP and upgrade cost compared to BSU and other variations of CSU.

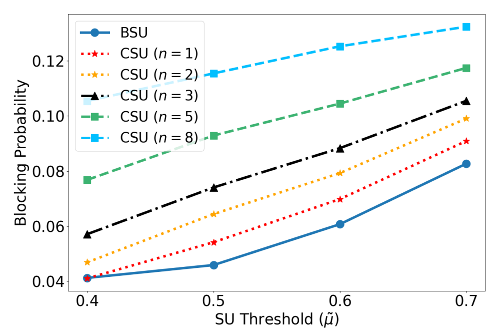


Fig. 3. Blocking probability comparison of CSU and BSU.

### *C. CLU vs. Baseline Approaches*

In Fig. 5, we evaluate the performance of CLU and analyze the trade-off between BP (blue solid line) and upgrade cost (red dashed line). In addition to comparing with CSU ($n = 3$) (as discussed in Section IV-B), we also consider two extreme cases: Early Upgrade (EU) and No Upgrade (NU). EU initiates network operation by upgrading all links without considering any selection criteria which leads to highest cost (512 units) with lowest blocking. In NU, the entire network operates only

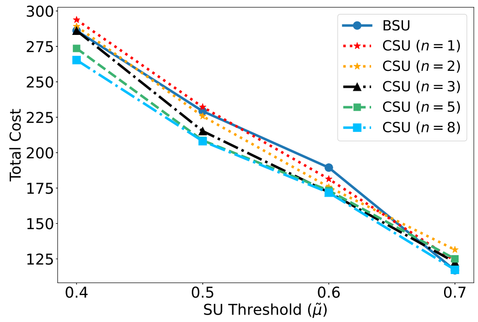


Fig. 4. Upgrade cost comparison of CSU and BSU.

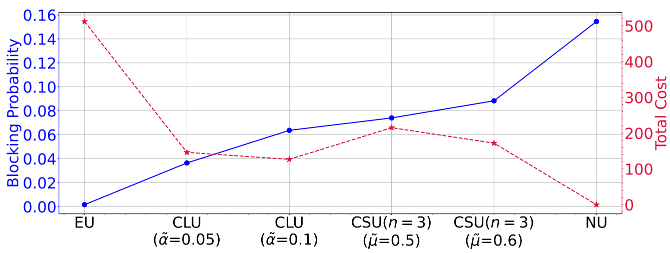


Fig. 5. Comparison of CLU with baseline strategies.

in C band without any upgrade, which leads to highest BP (about 16%) and lowest upgrade cost.

In Fig. 5, our strategy CLU outperforms CSU ($n = 3$) for different values of $\tilde{\mu}$. With $\tilde{\alpha} = 0.05$, CLU leads to lower BP of about 4% compared to about 7% and 9% BP by CSU for $\tilde{\mu}$ = 0.5 and 0.6, respectively. CLU also significantly curtails upgrade cost by about 32% and 15% compared to CSU for $\tilde{\mu}$ = 0.5 and 0.6, respectively. As CBPL threshold is increased, i.e., $\tilde{\alpha}$ = 0.1, CLU delays the upgrade lowering the cost slightly but it leads to higher BP of about 6% (which is still lower than BP of CSU). In terms of cost savings, CLU reduces upgrade cost by about 41% and 26% compared to CSU for $\tilde{\mu}$ = 0.5 and 0.6, respectively. It is evident that increasing SU threshold reduces upgrade cost at the expense of increased BP. Hence, a network operator could benefit from using CLU, which reduces both BP and upgrade cost compared to CSU.

TABLE I
NUMBER OF LINKS UPGRADED PER YEAR

| Method \ Year | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BSU | $\tilde{\mu}$ = 0.5 | 2 | 1 | 1 | 2 | 3 | 2 | 2 | 3 | 2 | 0 | 18 |
| | $\tilde{\mu}$ = 0.6 | 1 | 1 | 1 | 1 | 2 | 1 | 2 | 2 | 2 | 0 | 13 |
| CSU ($n = 3$) | $\tilde{\mu}$ = 0.5 | 0 | 0 | 1 | 1 | 1 | 2 | 3 | 4 | 4 | 0 | 16 |
| | $\tilde{\mu}$ = 0.6 | 0 | 0 | 0 | 1 | 1 | 1 | 2 | 3 | 5 | 0 | 13 |
| CLU | $\tilde{\alpha}$ = 0.05 | 0 | 2 | 4 | 3 | 0 | 0 | 0 | 1 | 0 | 0 | 10 |
| | $\tilde{\alpha}$ = 0.1 | 0 | 0 | 2 | 4 | 2 | 1 | 1 | 0 | 0 | 0 | 10 |

To analyze the impact of upgrades at appropriate times, Table I compares the number of links upgraded in a year by each strategy. We see that BSU and CLU start upgrading at year 1 and 2, respectively, while CSU starts at year 3. For CSU, since upgrades are delayed by $n = 3$ times, most link upgrades occur much later, e.g., at year 6 and beyond. As shown in Table I, with increasing $\tilde{\mu}$, fewer links are upgraded by the baseline strategies (since not all links in the network reach the SU threshold). For example, for $\tilde{\mu}$ = 0.5, 18 and 16 links are upgraded by BSU and CSU, respectively, whereas 13 links are upgraded for $\tilde{\mu}$ = 0.6. On the other hand, we show that CLU significantly outperforms both BSU and CSU as it upgrades only 10 links in appropriate years for $\tilde{\alpha}$ = 0.05 and 0.1. In Fig. 2, we show which 10 links in the topology are upgraded by CLU for $\tilde{\alpha}$ = 0.05 in years 2, 3, 4, and 8.

## V. Conclusion

We proposed a novel upgrade strategy, named CLU, utilizing a RNN-based model that effectively identifies links for upgrade in the network. Numerical results show that our proposed strategy outperforms the baseline strategies in terms of both BP and upgrade cost. These findings highlight the potential for significant cost savings and reduced BP when a network operator employs a trained ML model for upgrade decision. Future work should consider a robust physical-layer model to achieve a more comprehensive analysis of the behavior of CLU under dynamic conditions.

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