Load-Aware Nonlinearity Estimation for Efficient Resource Allocation in Elastic Optical Networks

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***Abstract*— Elastic optical networking has emerged as a promising technology to accommodate high-capacity and dynamic bandwidth demands of next-generation wireless networks. However, the nonlinear impairments affect the network performance in terms of system reach distance, spectral efficiency and network utilization. The nonlinear impairments are currently assigned a fixed reference margin based on a worst case estimation which results in sub-optimal spectrum utilization. Therefore, in this paper, we propose a novel load-aware nonlinearity estimation model which is more accurate compared to the fixed reference margin and is shown to reduce request blocking ratio. We further present a routing, modulation and spectrum assignment (RMSA) solution using the proposed nonlinearity model. The integrated approach of our RMSA solution is evaluated for dynamic service requests with single and mixed line-rate traffic demands over the National Science Foundation Network (NSFNET) topology. The results presented in this paper validate the benefits of our novel nonlinearity estimation model and the proposed algorithm in terms of service blocking ratio and spectrum utilization.**

Keywords—nonlinear impairments estimation, RMSA, elastic optical networks.

I. INTRODUCTION

The significant challenge faced by service providers to support dynamic traffic demands over 5G network infrastructure requires agile optical core networks. The convergence of wireless and optical networks as envisaged in the 5G architectures will introduce a lot of traffic dynamics to the optical access, metro as well as core networks [1]. Contemporary methods of resource provisioning in the optical metro and core networks are not efficient for the dynamic instantiation of services with flexible bandwidth granularities ranging from hundreds of megabits to terabits per second. These requirements pose a significant challenge to the planning and operations of optical backbone networks. In this context, elastic optical networks (EON) is a promising technology that can address the challenges, by enabling programmable features on optical devices and components. EON technologies enable higher network utilization by supporting flexible bandwidth granularities [2] [3]. However, in order to exploit the benefits of EON and achieve higher spectral efficiency, we need complex control mechanisms that monitor/estimate network states and optimize resource allocation.

The spectral efficiency of optical systems depends directly on signal to noise ratio (SNR) which is affected by various linear and nonlinear effects introduced by devices, components and transmission signals themselves. The linear effects such as power loss, chromatic dispersion (CD), polarization-mode dispersion (PMD) can be compensated using affordable techniques whereas nonlinear impairments (NLI) such as self-phase modulation (SPM), cross-phase modulation (XPM), four-wave mixing (FWM), stimulated and Raman scattering (SRS) and stimulated Brillouin scattering (SBS) are difficult to mitigate using commercial feasible technologies. Therefore, nonlinear effects are an important factors in the estimation of SNR. In fixed-grid WDM systems, NLI are generally assigned a reference margin (RM) to calculate the SNR of the links/paths [4] [5]. Assigning a fixed reference margin to NLI is useful if the accurate monitoring/estimation information is not available and it also avoids extensive computations before provisioning new requests since it already considers the worst case link conditions. However, the RM approach to NLI reduces the SNR budget for most of the connections which leads to more conservative modulation formats. This results in underutilization of spectral resources.

In order to improve network wide spectrum utilization under the effects of optical impairments, there are various impairment-aware RSA techniques proposed and studied in the literature [3] [6] [7]. In this paper, we specifically focus on an NLI estimation model that considers the state of the link such as channel occupancy and power spectral density (PSD). However, assigning spectrum and modulation formats based on exact nonlinearity impairments results in future requests introducing more nonlinear noise that affects established requests. In [8], the authors show that accurate NLI calculation results in much more blocking of future requests in order to protect existing services from additional nonlinear effects than worst NLI estimation. Thus in our work, we do not consider the performance of accurate NLI estimation. In [9], the blocking is prevented by using expensive digital regenerators at certain locations within the network to allow more flexibility with spectrum allocation. However, digital regenerators are cost prohibitive [10] and optical-electronic-optical conversion also adds additional latency.

In this paper, we propose a hybrid nonlinear impairments (HN) estimation technique based on the Gaussian noise (GN) model [11] instead of RM method or channel occupancy based exact nonlinearity calculation. The HN model provides close-to-accurate estimations of NLI which improves the spectrum utilization at reduced computational complexity. First we show that the HN model improves network utilization for sequentially loaded traffic requests and further propose an enhanced version of the algorithm called nonlinearity-aware resource allocation (NARA) algorithm to serve dynamic traffic requests. We compare our HN approach with the RM approach through extensive simulation studies over NSFNET topology under different traffic models.

In the rest of the paper, Section II explains the problem of exact NLI estimation and RM method and also describes our HN model along with its advantages. In Section III, we explain our RMSA algorithm along with an example scenario. Section IV describes the simulation setup for the evaluation of our proposed algorithms and results obtained while Section V concludes the paper.

II. Hybrid Nonlinearity Estimation Model

In this section, we describe the deficiencies of existing approaches of nonlinear impairment estimation and propose a novel hybrid nonlinearity estimation model. Following assumptions are made: (i) transparent dual-polarization optical system using coherent detection without inline compensation and with all optical CDC ROADM based switching; (ii) PMD and PDL are ignored while CD is compensated by DSP techniques at receivers; (iii) rectangle signal spectrum shape and no guard band between channels; (iv) NLI accumulates incoherently along spans; (v) equal transmission PSD among different channels; (vi) power loss is completely compensated by erbium doped fiber amplifiers (EDFA) within a fiber span or at optical switching element; (vii) completely tunable, bandwidth variable and modulation format adaptable transceivers.

The amplified spontaneous emission (ASE) and NLI are dominant impairments during transmission and hence the SNR at receiver is calculated as:

$$SNR_{Rx} = P_{ch}/(P_{ASE} + P_{NLI}) \tag{1}$$

where P_{ch} is channel launch power, P_{ASE} and P_{NLI} are the power of ASE noise and NLI within channel respectively. The power of ASE noise [12] within received channel bandwidth is calculated as:

$$P_{ASE} = 10^{\frac{NF}{10}} \cdot h\nu \sum_n (10^{\frac{A_n}{10}} - 1) \cdot R \tag{2}$$

where NF is the noise figure for amplifier, h is Planck's constant, ν is signal frequency and R is the baud rate of the signal. A_n stands for signal loss during transmission including span loss and node insertion loss. All the loss are assumed to be completely compensated by EDFAs.

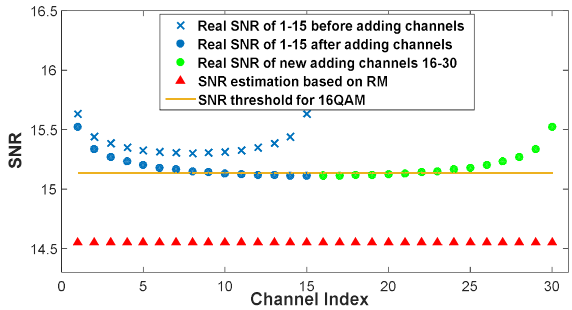


Fig. 1. SNR analyses by adding new channels.

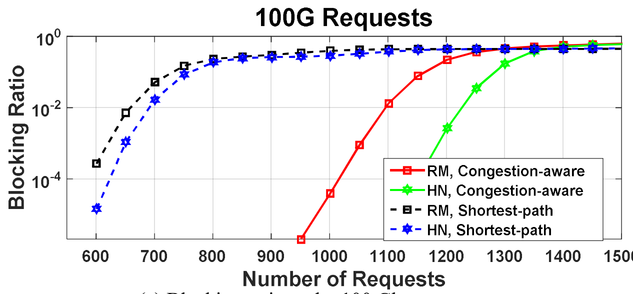
While ASE has a simple model, traditional NLI models are complex. In optical WDM systems, the traditional way to measure optical link performance is to calculate the system reach distance based on the link budget [5]. In [4] and [5], the authors consider practical principles of DWDM system design and engineering where they assign 0.5 dB SNR reference margin for SPM, XPM, FWM and SRS/SBS separately to account for their impact. 2 dB SNR margin accounting for NLI is also adopted in [13]. Similar to the RM method, the LOGON strategy in [14] and the nonlinearity estimation method in [15] calculates NLI in the worst case using GN model assuming full spectrum occupancy which also corresponds to approximate 2dB loss.

In Fig. 1, we showcase the effects of real NLI (using GN model) and RM method (2dB) on the SNR of the services provisioned on the same link. Services are provisioned over an 18 spans fibre (80 km/span) deploying single mode fibre with fibre loss coefficient of 0.22 dB/km, fibre nonlinear coefficient of 1.3 $W^{-1}km^{-1}$ and chromatic dispersion coefficient of 16.7 $ps \cdot nm^{-1}km^{-1}$. Noise figure for all EDFAs is set to be 5 dB and insertion loss for the ROADMs is 7.25 dB. Transmission signal PSD is set to be 19 mW/THz. It can be seen from Fig.1 that when only 15 channels (blue cross on the left, channels 1-15) continuously occupy the link, all channels are able to utilize 16QAM for transmission based on their real NLI. However, when more services are provisioned using channels 16-30, the NLI of established channels 1-15 increase and services in channel 11-15 can no longer support 16QAM resulting in inter-channel blocking. In case of RM method 16QAM is not possible for all channels in both cases since it largely overestimates the NLI impacts.

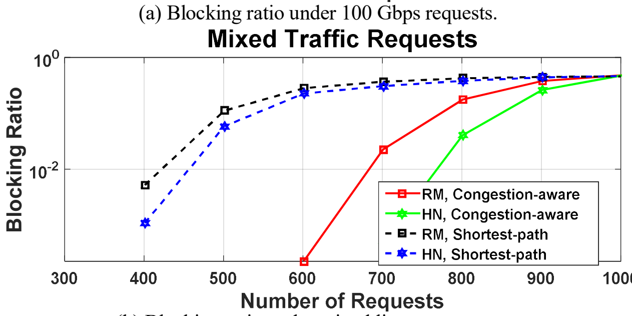
Therefore the RM approach to NLI estimation is also not efficient for EON, as they can support flexible channel allocation to accommodate dynamic bandwidth requests [2]. Overestimating nonlinear impairments results in some service requests using conservative modulation formats which reduces the overall spectral efficiency. In order to overcome the disadvantages of the conservative RM method and inter-channel blocking occurring due to real-time NLI estimation, we propose a hybrid nonlinear impairment estimation model in this paper. We define five loading states (LS) of the link as being 20%, 40%, 60%, 80% or 100% occupied by continuous spectrum slots. NLI for above five states are pre-calculated using the GN model with continuous spectrum assignment for each service. This leads to maximum NLI estimation for each request within the certain LS. When more requests are provisioned on the link within certain LS, NLI are always over-estimated reasonably while allowing improved SNR budgets specifically during low channel occupancy. In this way, the HN approach combines features of both conservative RM method and greedy exact nonlinear impairment estimation method. As the LS of the link changes, NLI estimation of the link changes and services provisioned over that link may also be affected. If any services are blocked due to LS change, affected services are required to be reconfigured.

To validate the benefits of HN model, we compare the performance of the HN model with the RM model in terms of service acceptance ratio for different traffic models over NSFNET topology. The first traffic model contains only 100Gbps traffic requests while the other consists of mixed traffic requests of 400 Gbps, 100 Gbps, 40 Gbps and 10 Gbps (equal number of each bandwidth granularity). Both traffic models are sequentially loaded to the optical network (no expiration). Fig. 2 shows the average blocking ratio of the HN solution and the RM solution for number of requests. It depicts that the HN model is able to achieve higher service acceptance ratio than the RM method. In case of congestion-aware routing strategy [15], HN accepts approximately 130 more 100G requests than the RM solution at 1% blocking ratio as shown in Fig. 2(a). Similarly, as shown in Fig. 2(b) HN accepts approximately 100 more requests in case of mixed-traffic demands.

The results presented in Fig. 2(a) and (b) clearly showcase the benefit of HN model over the RM model. In order to further enhance our proposed solution, in the following section, we describe a complete RMSA solution which utilizes the HN model for dynamic traffic requests.



(a) Blocking ratio under 100 Gbps requests.



(b) Blocking ratio under mixed line-rate requests.

Fig. 2. Requests blocking ratio.

III. Nonlinearity-Aware Resources Allocation

In order to protect established services and allow future requests while improving the spectrum utilization, we propose a novel nonlinearity-aware resource allocation (NARA) algorithm based on K-least congested path routing with HN model (KLC with HN) for dynamic traffic requests using first-fit spectrum assignment. Similar to congestion-aware routing in [15], the weight W_j of the link j is calculated as:

$$W_j = N_{span,j}/(1 - \frac{Ss_j^{oc}}{Ss_j}) \qquad (3)$$

where $N_{span,j}$ is the number of fibre spans on the link j, Ss_j is the total number of spectrum slots and Ss_j^{oc} is the number of occupied spectrum slots of the link j respectively.

In our algorithm, we assume that each service request R consists of traffic demand r bits/second from source S to destination D with certain time of arrival and holding time. The network state (NS) that is used for computation includes LS, weight and spectrum occupancy of each link in the network. For each new service request, NARA algorithm computes a solution using KLC with HN algorithm. As shown in the KLC with HN algorithm, for each request R_i, we calculate K-least congested paths between source S_i and destination D_i based on the current NS. Further, for each calculated path $P_{k,i}$ we compute $SNR_{k,i}$ according to the LS of each link of the path and select the optimal modulation format $MF_{k,i}$ to minimize required spectrum for the request r_i. The first available spectrum resource on all links of the path $SR_{k,i}$ is then assigned to the request. In order to facilitate more future requests, the cost of each candidate path is calculated as shown in equation (4)

$$Cost_k^i = N_{sr,k}^i \cdot N_{link,k}^i \qquad (4)$$

where $N_{sr,k}^i$ and $N_{link,k}^i$ are the number of required spectrum slots and number of links of the path k respectively. Equation (4) captures the total utilization of spectrum resources along the path and hence selecting minimal cost path facilitates higher spectrum utilization across the network.

KLC with HN Algorithm

Input : Request R_i, NS
Output : RMSA solution for the R_i

Find K least congested paths $\{P_{k,i}\}$ for r_i using graph edge weight given in eq. (3), ($k = 1, 2, \ldots, K$);
for path $P_{k,i}$
  Calculate estimated $SNR_{k,i}$ based on HN model;
  Apply optimal modulation format $MF_{k,i}$;
  Based on $MF_{k,i}$, search for spectrum resources $SR_{k,i}$ that can satisfy traffic demand r_i;
  if spectrum resources $SR_{k,i}$ are available;
    Record $P_{k,i}$, $MF_{k,i}$ and $SR_{k,i}$;
    Calculate cost of $P_{k,i}$;
  else set cost of $P_{k,i}$ to be infinity;
  end if
end for
if minimum cost $Cost_{m,i}$ is not infinity
  Choose the minimum cost path $P_{m,i}$;
  return $P_{m,i}$, $MF_{m,i}$, $SR_{m,i}$;
else reject the request R_i; **return** fail;
end if

The NARA algorithm considers the effects of the new service provisioning on established services if LS of links along the selected path changes. If LS changes and the SNR of existing services drops below their SNR threshold (see Table 1), inter-channel blocking occurs and the affected services are reconfigured using the KLC with HN algorithm. If reconfigured services lead to further inter-channel blocking, the new service request R_i is rejected to avoid significantly complex reconfiguration loops. Since we define only 5 LS for each link in the HN model, only a small number of reconfigurations are required. If all affected services are reconfigured successfully, the new request R_i is accepted by the NARA algorithm.

NARA Algorithm

Input : Service request, NS
Output : RMSA solution for the request

for request R_i
  Call KLC with HN algorithm for R_i;
  Reconfigure affected services using KLC with HN algorithm by their provisioning order if any established services are affected;
  if configuration of R_i and reconfiguration of all affected services (if necessary) are successful
    Accept R_i and affected services reconfiguration;
    Update NS;
  else reject request R_i;
  end if
  Release connection and resources when expired;
end for

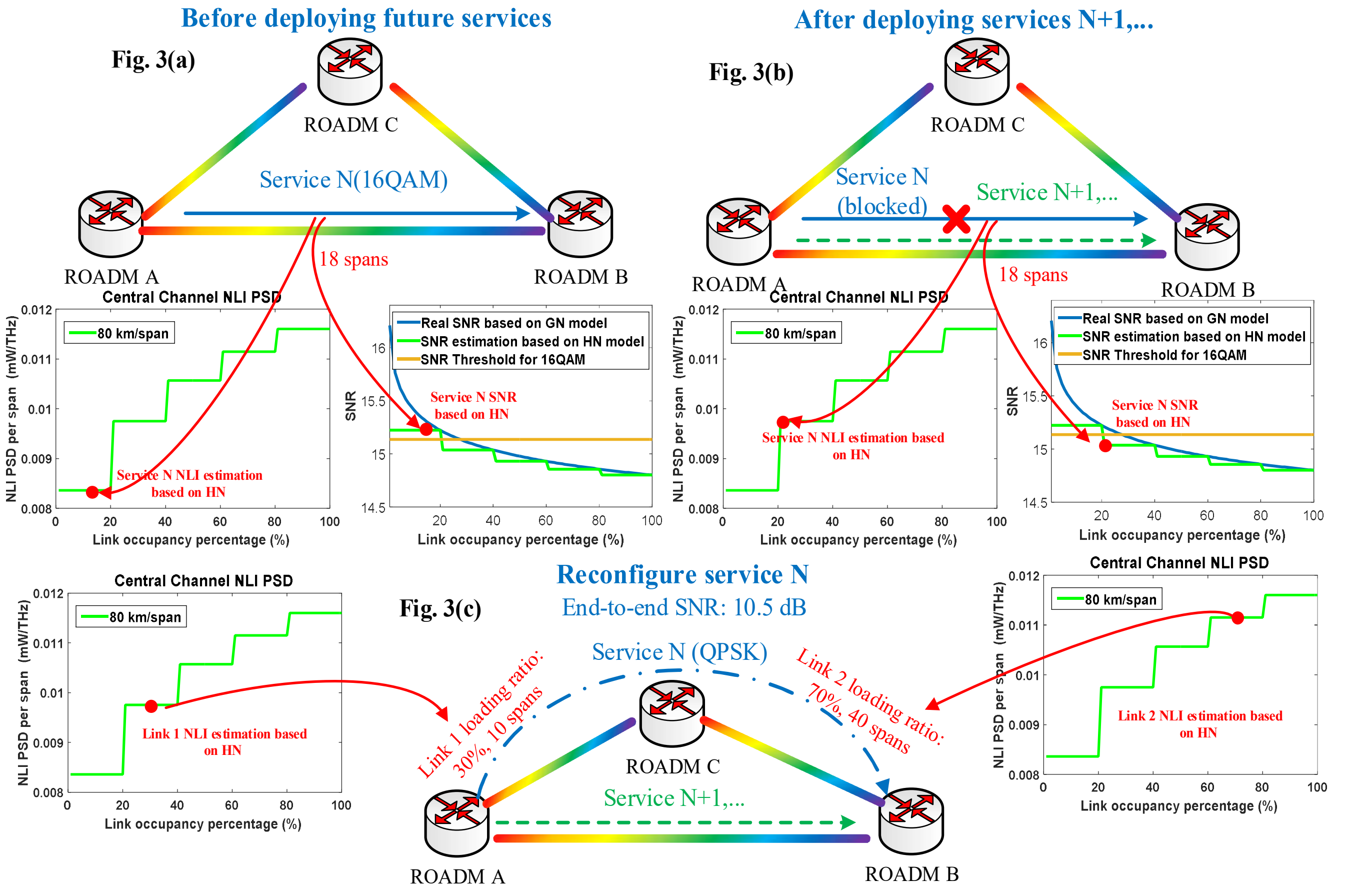


Fig. 3. Example of service reconfiguration of NARA algorithm.

Fig. 3 depicts the service reconfiguration scenario based on the NARA algorithm. As shown in Fig. 3(a), service N is provisioned on the 15% loaded link A-B which belongs to the 20% LS as per our HN model. The NLI PSD on link A-B for the central channel is calculated to be 0.0084 mW/THz per span based on HN model which results in the SNR of 15.22dB for service N. Based on this SNR value, service N is able to transmit a 16QAM signal from A to B as shown in Fig. 3(a). In Fig. 3(b), when more services are provisioned on the same link, the LS of link A-B changes which triggers the algorithm to check if any existing services using the link A-B are affected due to degraded SNR. In this case, service N can no longer transmit 16QAM signal and needs to be reconfigured. The NARA algorithm computes the new path A-C-B, as shown in Fig. 3(c) and determines the NLI for each link on the path based on their respective LS. The SNR is then calculated considering the cumulative NLI and ASE as per equation (1) which dictates the reconfigured modulation format.

IV. Simulation Setup and Performance Evaluation

In this section, we discuss the evaluation approach for the NARA algorithm and the simulation setup. We compare the performance of the NARA algorithm (KLC with HN using K to be 5) with the benchmark method that uses distance based shortest-path routing with 2dB RM. The service reconfiguration not required in benchmark due to assuming NLI to be worst case. The cumulative blocking ratio of requests and network spectrum utilization are evaluated in this paper as they represent important metrics for optical network planning solutions. In our simulation setup, we consider that the optical system operates in the 5THz bandwidth of C-band (from 190.6 THz to 195.6 THz) and 12.5 GHz granularity as per ITU–T G.694.1 v2.0 [15] corresponding to 400 spectrum slots. Multiple continuous frequency slots can be combined to form a superchannel. We use the same set of fiber and system parameters as described in Section II. The pre-FEC bit error rate is set to be $4{\times}10^{-3}$ at receiver and the required SNR for different modulation formats to achieve this pre-FEC BER is shown in Table 1:

Table 1. SNR requirements for pre-FEC BER of $\mathbf{4{\times}10^{-3}}$ under different modulation formats.

Modulation Format	Required SNR
PM-BPSK	5.46 dB
PM-QPSK	8.47 dB
PM-8QAM	12.45 dB
PM-16QAM	15.13 dB
PM-32QAM	18.12 dB
PM-64QAM	21.05 dB

In our simulation setup, we consider the NSFNET topology that consists of 14 nodes and 21 links as shown in Fig.4. Each service request consists of a randomly selected pair of nodes as source and destination with symmetric bi-directional data rate requirement (which includes overhead for forward error correction). Two types of traffic scenarios are considered in this evaluation: 1) all requests of 100 Gb/s and 2) mixed line-rate requests with 10% of them being 400 Gb/s, 40% being 100 Gb/s, 30% being 40 Gb/s and 20% being 10 Gb/s to study the effects of different bandwidth granularity requirements. The interval time of traffic requests is assumed to be Poisson distributed and the holding time is assumed to be exponentially distributed. Both average service interval time and average service holding time are varied to simulate dynamicity of the traffic. We generate 10000 requests for each traffic scenario. These requests are provisioned and the cumulative blocking ratio is calculated after all the requests. All scenarios are repeated 1000 times to obtain statistically relevant results.

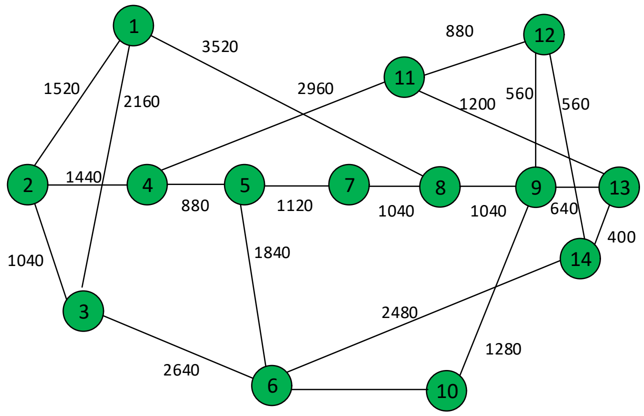


Fig. 4. NSF network topology (unit: km).

In Fig. 5, we showcase the cumulative blocking ratio for different average holding times. The average service interval time is set to be 1 time unit while average holding time is varied from 2000 time units to 8000 time units with 1000 time units increments. It can be seen that, the NARA algorithm achieves between 5% to 15% higher service acceptance ratio than the benchmark at a range of different holding times. As the average holding time increases, the blocking ratio increases as services with less average holding time expire sooner thus making more spectrum slots available for future services. The algorithm performs better in case of shorter average holding times compared to longer holding time under both traffic scenarios.

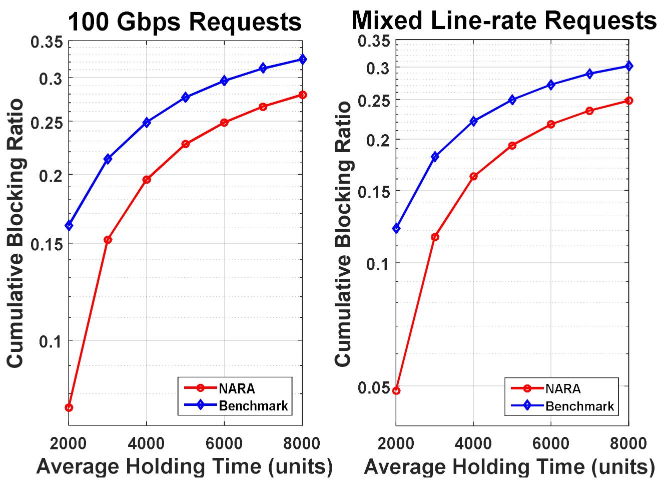


Fig. 5. Cumulative blocking ratio of different holding time.

To evaluate the effect of interval time of arrival requests, we fix the average holding time to be 8000 time units while varying interval time from 1 time unit to 6 time units. The cumulative blocking ratio in this case is shown in Fig. 6 where NARA experiences 5-10% less blocking compared to benchmark for 100 Gbps traffic request. The benefit of the algorithm in terms of blocking ratio increases as the requests interval time increases. This is because with shorter average interval time, more requests are provisioned in the network within a certain amount of time, which makes the network more congested. As a result, less services can be provisioned successfully even with the optimal solution. However, less network spectrum resources are required within the certain amount of time as the average service interval time increases. This leads to a less congested network thus more services are able to be provisioned with the NARA algorithm. There is no blocking with the NARA algorithm at interval time 6 whereas the benchmark solution has 10% blocking. In case of mixed line rate traffic requests, the NARA algorithm achieves approximately 5% improvement over benchmark solution for all interval time.

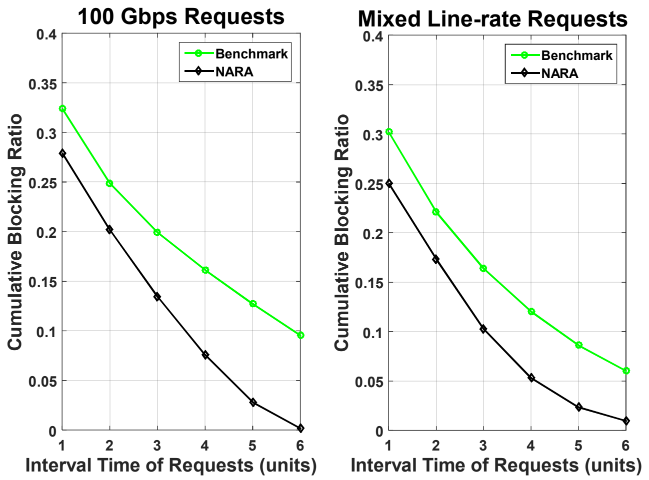


Fig. 6. Cumulative blocking ratio of different interval time of requests.

Fig. 7 shows the comparison of average network spectrum utilization between the NARA algorithm and benchmark solution for different average holding times. We also plot the maximum and minimum spectrum utilization achieved during the 1000 instances of these traffic scenarios. The network utilization in this case is calculated as:

$$NU = \frac{\sum_j Ss_j^{oc}}{\sum_j Ss_j} \qquad (5)$$

NARA is able to achieve 4.5% to 6.72% more network spectrum utilization at the 10000 request mark than the benchmark solution for 100 Gbps requests. In case of mixed traffic requests, again the algorithm achieves 4.94% to 6.22% more spectrum utilization for different holding times. Higher spectrum utilization in NARA is primarily due to the use of the HN model for more accurate nonlinearity estimation but also the K-least congested path routing achieves better path selection to avoid more congested path as well.

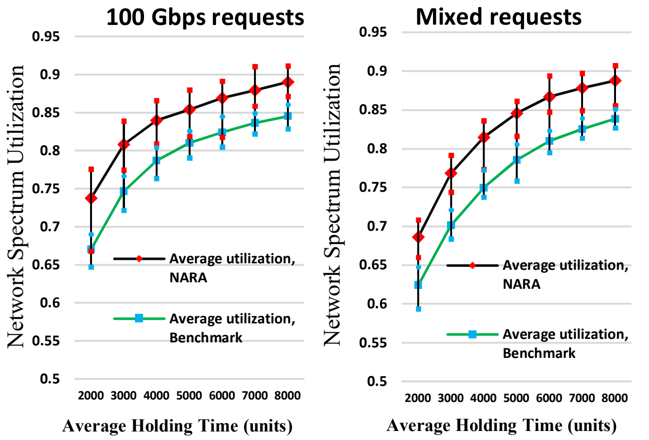


Fig. 7. Average network spectrum utilization of different holding time.

For mixed traffic requests, the percentage improvement in number of accepted requests for the NARA algorithm over the benchmark method is shown in Fig. 8. This graph demonstrates that at least 5% improvement is achieved for all traffic demands. In case of smaller service holding time, the improvement in larger traffic requests (100 Gbps and 400 Gbps) is significantly higher from 11% to 13% since the NARA algorithm assigns more continuous spectrum resources than the benchmark solution. However, as the holding time increases, the network becomes more congested reducing the amount of continuous spectrum resources along the path. In this case, large traffic requests that require more continuous spectrum resources are more difficult to provision compared to small traffic requests. This effect is also evident from Fig. 8 where the NARA algorithm favors the smaller traffic requests (10 Gbps and 40 Gbps) over large traffic requests and achieves 7% to 9% improvement in acceptance of small traffic requests.

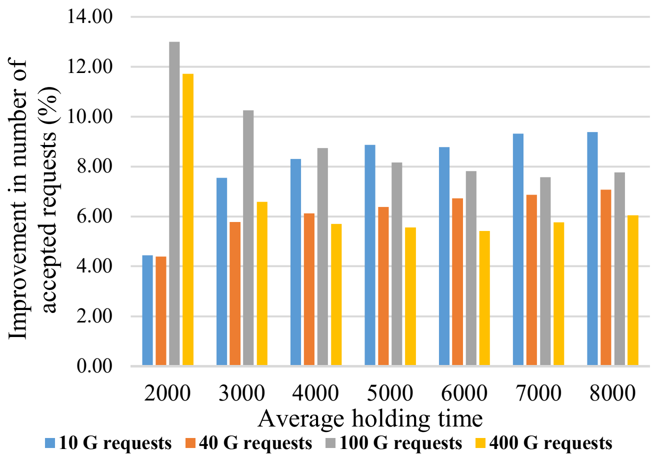


Fig. 8. Accepted traffic improvement for NARA compared to benchmark.

V. Conclusion

In this paper, we have proposed a novel hybrid nonlinearity estimation model for elastic optical networks. The proposed model provides improved accuracy compared to existing fixed reference margin method and it is also computationally simpler than the accurate nonlinearity estimation method. The nonlinearity-aware resource allocation algorithm proposed in this paper utilizes the HN model along with a sophisticated K-least congested path routing strategy. The NARA algorithm is compared with a benchmark solution using extensive simulation studies for different traffic models. The results show that the NARA algorithm significantly improves service acceptance ratio and network spectrum utilization which makes it appropriate for elastic optical network planning and operation.

Acknowledgment

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