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Advanced Resource Allocation Strategies for MCF-based SDM-EONs: Crosstalk Aware and Machine Learning Assisted Algorithms

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ABSTRACT In space division multiplexed elastic optical networks (SDM-EONs), parallel transmission of lightpaths is enabled using multicore fibers (MCFs) in the network. However, the intercore crosstalk (XT) between parallel transmissions degrades the quality of service and reduces the utilization of available capacity. This impairment results in a tradeoff between spectrum utilization and XT accumulation. In this paper, we discuss various approaches to solve the routing, modulation, core, and spectrum assignment (RMCSA) problem while balancing the tradeoff, namely, Tridental Resource Assignment algorithm (TRA), and Spectrum Wastage Avoidance-based Resource Allocation (SWARM) algorithm. We also propose offline optimizations such as machine learning (ML)-aided threshold optimization, integer linear programming-based priority path selection (PPS) for routing, and customized weights in the tridental coefficient (TC) to improve the performance of TRA. The ML-aided optimizer and PPS improve the performance of "any" RMCSA algorithm. The customized weights in TC and intelligent resource selection strategy improve TRA even further. Extensive simulation experiments show significant reductions in bandwidth blocking probability, by several orders of magnitude for a variety of scenarios.
Keywords: SDM-EON, intercore crosstalk, resource allocation, machine learning, TRA, SWARM

1. INTRODUCTION

The increasing demands for bandwidth driven by Internet-of-Things, 5G and 6G communications, cloud-based services, and data center networks can be met by space division multiplexed elastic optical networks (SDM-EONs) [1]. SDM-EONs enable parallel transmission of optical signals through multicore fibers (MCF) with distance-adaptive multicarrier transmission. However, signal transmission through MCF is degraded by intercore crosstalk (XT) between weakly coupled cores which is significant enough to affect the quality of transmission (QoT), leading to dropping of connections and loss of data [1]. Routing, Modulation, Core, and Spectrum Assignment (RMCSA) is a fundamental SDM-EON planning problem, which involves assigning lightpaths with appropriate spectral bandwidth to traffic demands [2]. Ensuring the QoT of each prospective lightpath is within bounds is crucial for determining the viability of an SDM-EON RMCSA solution prior to deployment.

In RMCSA problem, each combination of modulation, core and spectrum results in a distinct XT accumulation and spectrum utilization. The higher modulations require less spectrum to carry the data but are highly XT-sensitive, whereas lower modulations require more spectrum to carry the same data but are less sensitive to XT. Similarly, parallel transmission over a core with more adjacent cores results in higher XT accumulation. In addition, the selection of spectrum intensifies or decreases the XT accumulation in the dynamic environment based on the location of the spectrum. In this paper, we first present two online RMCSA algorithms, Tridental Resource Assignment algorithm (TRA), and Spectrum Wastage Avoidance-based Resource Allocation (SWARM) algorithm. TRA selects the best candidate modulation-core-spectrum triplet using the concept of Tridental Coefficient (TC) [2]. SWARM on the other hand selects the best modulation-core-spectrum in a more computationally efficient manner by balancing the spectrum-XT tradeoff. We also present two offline solutions – mixed integer linear programming (MILP) for load balancing on paths, and machine learning (ML)-aided optimization. Interestingly, these offline approaches guarantee improvement in the performance of *any* RMCSA algorithm.

The paper is organized as follows. The problem statement is discussed in Section 2, and the proposed solutions are presented in Section 3. Section 4 presents the simulation results and Section 5 concludes the work.

2. PROBLEM STATEMENT

In an MCF-based SDM-EON, the QoT of a connection degrades due to XT from other parallel transmissions on adjacent cores. The level of degradation depends on the number of those parallel transmissions and the selected modulation. More transmissions cause more degradation and higher modulations are more XT sensitive.

In RMCSA problem, the modulation, core, and spectrum are selected for assignment on the route between source and destination nodes while satisfying the XT constraints. Every connection is established only when three conditions are satisfied as given in Def V.1 in [3]. The conditions are: a) the spectrum must be free, i.e., not occupied by any other connection, b) the spectrum can accommodate the selected modulation as per its

XT sensitivity, and c) establishment of the connection should not affect the ongoing connections based on the XT sensitivity of *their* modulations. The level of XT experienced by a connection on a core depends on how many adjacent cores have ongoing connections on overlapping spectrum. Thus, for a given modulation, the total possible XT can be different. In addition, the XT tolerance of the modulation decides which core and spectrum choice can be used. This is because higher modulations are more XT-sensitive whereas lower modulations can tolerate more XT. The selection of modulation determines how much spectrum is required for a given datarate - a higher modulation takes less spectrum. In RMCSA problem, the current selection of resources to carry connection data, which is modulation-core-spectrum, affects the occupancy of resources in the future for other connection requests. Thus the XT constraints to maintain the QoT of the current connection decide whether the overlapping spectrum(s) on adjacent cores can be occupied by incoming connections and what modulations are allowed to carry those connections. This shows that the selection of core and modulation results in the tradeoff between XT accumulation and spectrum utilization.

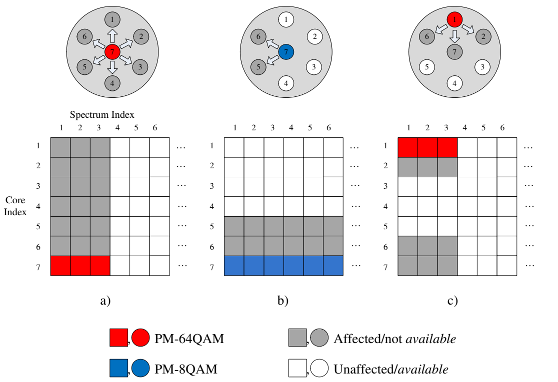

Figure 1: Tradeoff between XT tolerance and spectrum utilization based on choice of core and modulation.

We explain the tradeoff with the help of an example. Fig. 1 shows how modulation and core selection affect a 7-core MCF link. There are two polarization multiplexed (PM) modulations: PM-64QAM and PM-8QAM. When PM-64QAM is selected 3 frequency slots (FSs) are required and the overlapping spectrum on none of the adjacent cores is allowed to be occupied due to its high XT sensitivity whereas when PM-8QAM is selected the spectrum requirement is 6 FSs and the overlapping spectrum on four of the adjacent cores is allowed to be occupied [2], [4]. Here, the overlapping spectrum on adjacent cores that is not allowed to be occupied is denoted as affected/not available. As illustrated in Fig. 1a, when PM-64QAM on core 7 is assigned, the overlapping spectrum on any adjacent core cannot be filled as long as this connection remains in the network. Thus, the total spectrum occupied is 3×7=21 FSs. Similarly, In Fig. 1b, PM-8QAM on core 7 requires 18 FSs (=6×3). Thus, PM-8QAM is a better choice than PM-64QAM in this scenario despite its lower spectral efficiency. However, instead of core 7, if core 1 is selected for PM-64QAM, the required spectrum is now 12 FSs (=3×4), as shown in Fig. 1c. Thus the selection of modulation-core pair trades spectrum usage for lower XT levels and vice versa.

In this paper, we present the two RMCSA algorithms, TRA and SWARM, which balance this tradeoff in different ways and assign resources to the connections. TRA calculates a tridental coefficient (TC) to each combination of modulation-core-spectrum and then chooses the one with the lowest TC. The SWARM algorithm quantifies the tradeoff and then tries to reduce it. Finally, we present two offline approaches to improve the performance of any RMCSA algorithm including TRA and SWARM. We show a better routing by assigning weights to the paths to achieve load balancing, and present a machine learning-aided optimization approach to balance the tradeoff. We also present a third offline approach to optimize the weights of the TC.

3. PROPOSED SOLUTIONS

We first present the online RMCSA algorithms, TRA and SWARM, to select resources. We then present the offline optimizations. The common aim in the use of these tools is to balance the tradeoff between XT accumulation and spectrum utilization.

3.1 Dynamic/Online Methods

The RMCSA algorithm chooses route, modulation, core and spectrum for the incoming connection while making sure that the XT constraints are met to maintain the QoT of the connection. TRA provides a heuristic solution to solve the RMCSA problem with the help of TC. The word "Tridental" refers to three parameters - capacity loss, spectrum utilization, and location of the spectrum - which are normalized and added up to get the TC [2], [3]. Capacity loss [3] of a candidate resource quantifies the decrease in the network's capacity to accommodate future connections because of the assignment of the candidate resource to the incoming connection. We also found that TRA is versatile in capturing the network information to make a decision and so it also works well for translucent networks [2]. TRA uses an offline component to choose the best route called path priority based selection (PPS) which is explained in Section 3.2.

In addition to TRA, we present the SWARM algorithm. TRA explores all the resource choices to select the best resource choice. This process is computationally intensive and time consuming. SWARM mitigates this in two ways. First, it reduces the number of choices by grouping cores based on the number of the adjacent cores and using the first fit policy in the selection of spectrum. Second, it uses SWARM coefficient instead of TC to calculate the quantified tradeoff and then makes the decision based on SWARM coefficient. Similar to TRA, it balances the tradeoff and outperforms other algorithms while being faster than TRA.

3.2 Static/Offline Methods

The RMCSA algorithms run online, i.e., when connection requests arrive to the network. We present three offline approaches two of which help improve the performance of any online RMCSA algorithm and the last helps improve the performance of TRA. The first approach is to calculate path priorities for multiple candidate paths for each source-destination (s-d) pair or route. These priorities are then used for online resource assignment for the MCSA part. The path priorities are determined based on path probabilities that optimize the link load on the precomputed K-shortest paths (KSPs) for each s-d pair. A Mixed Integer Linear Programming (MILP) problem is solved offline to determine the path probabilities [2], [3]. The KSPs are prioritized based on higher to lower path probabilities, and this approach is referred to as priority-based path selection (PPS). The objective of the MILP is to minimize the sum of the average link load and the maximum link load.

The second approach is to use machine learning (ML) to get the litcore thresholds to control the selection of modulation formats which in turn improves the tradeoff balancing [4], [5], [6]. Here, litcore refers to an adjacent core on which the overlapping spectrum is occupied, and litcore threshold is the maximum number of adjacent cores on which the spectrum can be occupied. The ML model learns the underlying relationship between network features and corresponding output labels for better selection of core-modulation-spectrum. Here the features are set of litcore threshold for each modulation and the label is corresponding bandwidth blocking. This approach differs from others as it has faster convergence, can potentially improve the performance of any RMCSA algorithm for any network model in MCF-based SDM-EONs and can improve the execution time of decision making of any RMCSA algorithm.

The final approach is to optimize the weights in TC. The TC as shown in [2] is the sum of three terms - capacity loss [3], spectrum utilization, and location of the spectrum [2]. We used two weights α and β such that capacity loss is weighted by α, spectrum utilization by β and the location of the spectrum by (1 - α - β) and set the range as $0 \leq \alpha, \beta, (1 - \alpha - \beta) \leq 1$. Adjusting these weights changes the performance of TRA. We use a two-step process where we first execute TRA for different values of α and β for only 10% of the connection requests with extremely high load and finally get the set of α and β which offers the lowest bandwidth blocking.

4. SIMULATION RESULTS

We now present some simulation results for TRA and SWARM along with various baseline RMCSAs, and also show the performance improvement due to the offline methods for a variety of scenarios. We use generic German (DT) topology [3]. Each link has one MCF fiber with 7 cores deployed in both directions and each core has 4 THz of C-band spectrum with a slice width of 12.5 GHz, i.e., 320 frequency slots (S = 320). Connections arrive according to a Poisson process with exponential holding times of mean one time unit. In every iteration, we simulate 110,000 requests and use the first 10,000 connections to let the network reach steady state. 95% confidence intervals are obtained for each data point. The datarates are uniformly distributed between 40 Gbps to 400 Gbps with the granularity of 40 Gbps. 3 SPs are used for each s-d pair. We assume five modulations - PM-QPSK, PM-8QAM, PM-16QAM, PM-32QAM, and PM-64QAM. We consider average XT between two adjacent cores after a single span of propagation, denoted as XT_{μ}, of -40 dB. Transmission reach is the maximum distance which can be traversed with the selected modulation and the status of the overlapping spectrum on the adjacent cores. The transmission reach model corresponding to the XT_{μ} when transceiver is operating at 28 GBaud and span length is 50 km is used from [7] to get the litcore values.

We compare the performance of the proposed algorithms with the baseline XT-aware first fit algorithm (xtFF) , XT-aware first fit with exhaustive search over modulation algorithm (xtFM) and an algorithm from the literature precise XT (P-XT) [8]. xtFM chooses highest modulation (i.e., most spectrally efficient) for which the core and spectrum are available in first-fit fashion. P-XT does a XT-aware spectrum assignment with exhaustive search on all the routes. The spectrum available on the lowest index among the ones available on all the path-core pairs is selected. We also compare the performance of RMCSAs when offline optimizations are used. TRA uses PPS by default, pSWARM uses PPS, while rest of the algorithms use KSP. TRA-KSP is TRA with KSP. The RMCSA algorithms that are optimized using ML are denoted with '-ML'. TRA with optimized TC weights is denoted as oTRA.

Bandwidth blocking probability (BBP) performance is shown in Fig.2 and the corresponding distribution of modulations used is shown in Fig. 3. The optimized weights in oTRA are α=0.95 and β=0.05. It is clear that TRA and SWARM along with their variants outperform all the baseline algorithms. oTRA performs better than TRA while SWARM-ML and pSWARM-ML perform than all except TRA. TRA performs better than TRA-KSP which shows that the path priorities in PPS that are calculated offline help in load balancing, which in turn help TRA to perform even better. Interestingly, the ML-optimized variants of the RMCSAs perform better than their original versions indicating that ML helps with a judicious selection of modulations. From Fig.3, we can find that the better-performing RMCSAs have tend to use both higher and lower modulations. For all the algorithms except pSWARM, xtFF, TRA and its variants chooses the highest modulation and the first (i.e., lowest index) available slice window for assignment.

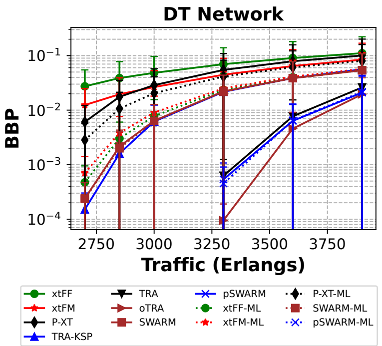

Figure 2: Variation of BBP for DT topology with C=7.

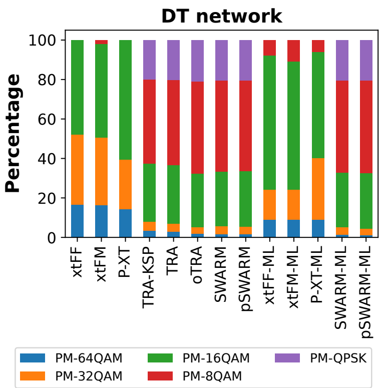

Figure 3: Distribution of modulations for DT topology with C=7.

The improvement in performance of P-XT with ML-aided optimization is larger than that of SWARM and pSWARM. The improvement provided by PPS in pSWARM is significant and is comparable to the performance improvement that ML-aided optimization provides to other RMCSAs. However, SWARM and pSWARM still show higher utilization of higher modulations compared to other RMCSAs, even with ML-aided optimization. This implies that SWARM and pSWARM are able to effectively utilize higher modulations in the presence of longer path lengths and litcore values, providing improved performance. The idea behind the selection of both higher and lower modulations is to help balance the tradeoff between XT sensitivity, which in turn results in various levels of XT accumulations, and spectrum utilization.

We conclude that TRA and SWARM along with their variants succeed in balancing this tradeoff than other RMCSA algorithms. Furthermore, the three offline optimizations are found to improve all algorithms' performance. The improvement in performance provided by PPS in pSWARM is significant, comparable to the gains obtained from ML-aided optimization in SWARM. The utilization of modulations is slightly increased with ML-aided optimization, indicating better spectrum efficiency, but SWARM and pSWARM still show higher utilization of higher modulations, implying effective utilization of resources in the presence of longer path lengths and litcore values. Finally, the utilization of various modulations show that with careful selection of modulations, the performance of the RMCSA can be improved.

5. CONCLUSIONS

We address the route, modulation, core, and spectrum allocation (RMCSA) problem in MCF-based SDM-EONs, with a focus on inter-core crosstalk. We present two RMCSA algorithms, Tridental Resource Allocation (TRA) and Spectrum Wastage Avoided Resource Management (SWARM). Three offline optimization tools, two of which are generic and can improve any RMCSA algorithm, and one to optimize the performance of TRA are also presented. Extensive simulations show that these algorithms outperform existing algorithms in the literature. The ML-aided optimization helps in selecting optimal thresholds on the number of occupied adjacent cores, thus effectively controlling the selection of modulations. Overall, our work contributes to the advancement of online RMCSA algorithms and showcases the potential of offline optimizations in improving the performance of online RMCSA algorithms.

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