Routing and Wavelength Assignment for Transparent Optical Networks With QoT Estimation Inaccuracies

Siamak Azodolmolky[1,2], Yvan Pointurier[2], Marianna Angelou[1,2], Josep Solé-Pareta[1], and Ioannis Tomkos[2]

[1]*Technical University of Catalonia, C/ Jordi Girona, 1-3. 08034 Barcelona, Catalonia, Spain.*
[2]*Athens Information Technology, 19.5km Markopoulo Ave., 19002 Peania, Athens, Greece.*
{siamak,marianna,pareta}@ac.upc.edu,{sazo, yvan, mang, itom}@ait.edu.gr

Abstract: We show how inaccuracies of Quality of Transmission (QoT) estimations, caused by imperfect models and lack of monitors in transparent optical networks, can be mitigated using a novel routing and wavelength assignment algorithm.

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1. Introduction

In transparent optical networks signals can propagate over long distances without electrical regeneration, causing physical layer impairments to accumulate and make lightpaths' Quality of Transmission (QoT) become potentially unacceptable. Impairment-Aware Routing and Wavelength Assignment (IA-RWA) is one technique to mitigate the impact of impairments and find lightpaths with acceptable QoT [1]. To assess the QoT of candidate lightpaths, most IA-RWA algorithms rely on a QoT estimator, a combination of analytical models and interpolations of measurements. QoT estimators inherit inaccuracies from imperfect modeling and measurement uncertainty.

Inaccuracies are inevitable yet undesirable; networks must be over-dimensioned to account for those uncertainties, leading for instance to a much higher regenerator deployment in translucent networks (with electrical regeneration capability) [2]. Similarly, in a transparent optical network, inaccurate QoT estimation may lead to lightpath acceptance while the lightpath QoT is actually unacceptable, or reject lightpaths with acceptable actual QoT, leading in each case to wastes of resources and time. Such uncertainties can be reduced by deploying additional monitoring equipments in the network, a solution which is not always economically feasible. However, if monitors are deployed in the network on some links then the QoT estimations using those monitor-equipped links will be more accurate. Hence the QoT margin required by the inaccuracies in general can be relaxed, allowing lightpaths to be properly established, while they would have been blocked if no monitoring equipment was present, thereby lowering the blocking rate. In this paper, we show that uncertainties have a dramatic impact on the network operation (in terms of blocking rate), but also that this impact can be mitigated using a novel IA-RWA, which appropriately accounts for QoT estimation uncertainties.

2. IA-RWA with consideration for QoT estimator uncertainties

The Q-factor is a metric highly correlated with BER that is used by many IA-RWA algorithms to estimate lightpaths' QoT [1]. Assuming perfect modeling and knowledge of systems parameters, an IA-RWA checks that the QoT estimate for a lightpath $\hat{Q}$ is above some predefined threshold Q_{th}, i.e. $\hat{Q} > Q_{th}$. However because of model and parameters uncertainties a margin should be added to Q_{th} such that the condition that $\hat{Q}$ should meet is really $\hat{Q} > Q_{th} + \eta Q_{EM}$ where $0 < \eta < 1$ is a factor that depends on the availability of monitoring information, and Q_{EM} is the maximum deviation that can be caused by the QoT uncertainties. We elaborate on the model for η next.

For a given link e, define $\Theta(e) = \sum_{k=1}^{n} \epsilon_k(e)(1 - m_k(e))$, where we assume that n different kinds of monitors are available (OSNR monitor, ...) and $m_k(e) = 1$ if a monitor of type k is deployed on link e, and $m_k(e) = 0$ otherwise. Considering the estimated Q-factor $\hat{Q}$ as a random variable that differs from the true Q-factor of a lightpath depending on what monitoring information is available to perform the estimation, we interpret $\Theta(e)$ as the variance of $\hat{Q}$ due to the uncertainty of parameters on link e, and each $\epsilon_k(e)$ as the contribution to the variance of $\hat{Q}$ due to the absence of monitor k on link e. We then define the adaptive factor $\eta(p)$ for a lightpath p as: $\eta(p) = \sum_{e \in p} \Theta(e)/\Theta_{\max}(p)$, where $\sum_{e \in p} \Theta(e)$ is the variance of $\hat{Q}$ accounting for uncertainties stemming from the absence of monitors on each link of the considered lightpath, and $\Theta_{\max}(p)$ is the maximum variance for the lightpath (i.e. no monitor on the lightpath). We now show how those lightpath-dependent QoT estimation inaccuracies can be alleviated in an IA-RWA algorithm. We adapt a multi-constraint path (MCP) selection algorithm to the specific problem of IA-RWA in transparent optical networks. The MCP algorithms find a path in a network subject to several simultaneous constraints: $\sum_{e \in p} w_m(e) < C_m; m =$

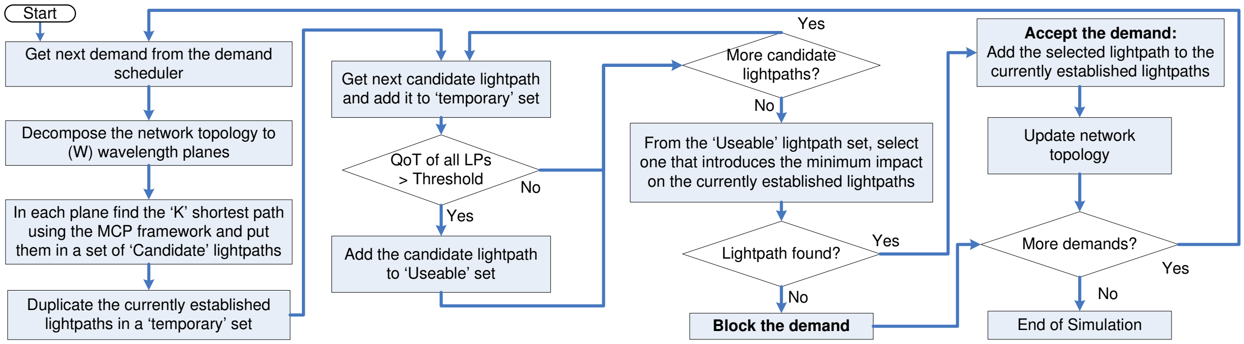

Fig. 1: Flow diagram of the Rahyab IA-RWA algorithm including QoT estimation uncertainties via a multi-constraint path framework.

$1, 2, \ldots, M$ where a link e is associated with a cost vector $w(e)$ of size M, costs are additive, and path costs are capped to predefined values C_m. Solving this problem is generally NP-complete for $M > 2$, but in the case of $M = 2$, it is shown in [3] that both constraints can be met simultaneously if the two costs w_1, w_2 are mapped to a single cost function $S(e) = f(w_1(e), w_2(e))$ as exhibited in [3]. Using the general framework in [3], in the context of IA-RWA with QoT uncertainties, we solve the MCP problem subject to two constraints:**1) Maximum lightpath length:** lightpaths over a certain length $L_{\max}$, which can be pre-computed, have no chance to have an adequate QoT, and should hence not be considered as candidate lightpaths; formally, $\sum_{e \in p} w_1(e) < L_{\max}; m = 1, 2, \ldots, M$ where $w_1(\cdot)$ denotes link length and **2) Maximum uncertainty:** the uncertainty on $\hat{Q}$ due to QoT estimation inaccuracies is $\eta(p) = \sum_{e \in p} \Theta(e)/\Theta_{\max}(p)$, which in turn is a function of the monitor availability. It is desirable to limit the uncertainty on $\hat{Q}$ to decrease the margin required on $\hat{Q}$ to establish lightpaths as explained above, hence the second constraint here is $\sum_{e \in p} \Theta(e)/\Theta_{\max}(p) < \eta_{\max}$ where $\eta_{\max}$ drives the maximum uncertainty $(\eta_{\max} Q_{EM})$ that the network manager is willing to tolerate in the network, or, equivalently, the minimum amount of monitoring that must be present on a lightpath to establish it.

Given this, we propose the "Rahyab" ("path finder" in Persian) IA-RWA algorithm depicted in Fig. 1. Each link is associated with a single weight $S(e)$ mixing the "link length" and "QoT estimator uncertainty" metrics as explained above. On a connection request arrival, we compute for each channel a predefined K number of candidate paths from source to destination using a shortest path algorithm considering single mixed metric $S(e)$ as the links weights. Therefore, the multi-constraint routing engine is exploited for finding paths (*candidate lightpaths*) that satisfy multiple constraints. Doing so separately for each channel ensures that the candidate lightpaths also conform to the wavelength continuity constraint. Once *candidate* lightpaths are determined, we construct another set of *usable* lightpaths by temporarily adding each candidate lightpath to the currently established lightpaths in the network and computing the impact of this addition on the QoT of already established lightpaths. If all QoT values are above the threshold the candidate lightpath under consideration is moved to the *usable* lightpath set. In this step, we use a custom QoT estimator that considers ASE noise, filter concatenation, PMD, node crosstalk, XPM, FWM. In the case where the *usable* set is empty, the demand is blocked, otherwise we select the lightpath that introduces the minimum QoT impact on the currently established lightpaths as in [4].

3. Comparative studies

We perform simulations to evaluate the performance of our algorithm on a 14-node national topology derived from the Deutsche Telekom network. We denote by "load" the total offered load to the network in Erlang assuming Poisson arrivals and exponentially-distributed durations. Links are SSMF spans (power: 3 dBm/channel, dispersion: 17 ps/nm/km, attenuation: 0.25 dB/km) with DCF (power: -4 dBm/channel, dispersion: 80 ps/nm/km, attenuation: 0.5 dB/km) undercompensating the dispersion by 30 ps/nm/km in each span. A pre-dispersion compensator sets the initial dispersion to -400 ps/nm and a post-dispersion compensator cancels residual dispersion at the end of each link. Amplifiers compensate exactly for the transmission losses (noise figure NF=6 dB with small random variations). The node architecture assumed here was adopted from [6] and the signal-to-crosstalk ratio is set to 32 dB with small random variations in each node. We assume 10 Gbps, and 50 GHz channel spacing. We set $Q_{th} = 15.5$ dB (corresponding to BER=10^{-9} without FEC), with a maximum uncertainty of $Q_{EM} = 1$ dB as in [2]. We compare "Rahyab" with two reference IA-RWA, K-SP-Q (with $K = 5$ alternate shortest paths) and MmQ, which do not consider QoT estimation inaccuracies [4],[5], with full monitoring deployment (a best case scenario for K-SP-Q and MmQ).

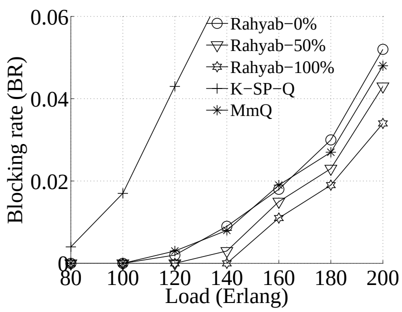

Fig. 2: Blocking rate vs. load ($W = 20$ channels per link).

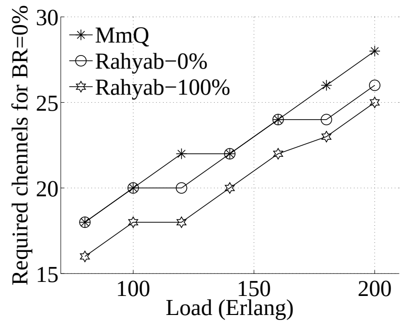

Fig. 3: Number of required channels to achieve 0% blocking.

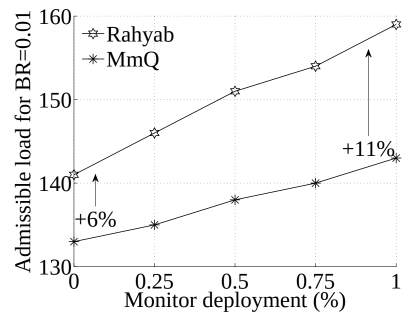

Fig. 4: Admissible load to achieve 1% blocking rate.

In Fig. 2 we vary the network load and show the blocking rate for the reference K-SP-Q and MmQ algorithms, and for "Rahyab" with different monitor deployment scenarios (deployment is assumed to be uniformly random). No and full monitor deployment cases are denoted as ("Rahyab-0%") and ("Rahyab-100%") respectively. The performance of K-SP-Q and MmQ should be compared with that of "Rahyab-100%". When there is no inaccuracy in QoT estimation (100% monitor deployment), the "Rahyab" algorithm is able to decrease the blocking rate thanks to the adaptive QoT margin. Rahyab-0%, for which no monitoring equipment is deployed, has a lower blocking rate than MmQ even though MmQ assumes full monitoring deployment. Indeed "Rahyab" uses alternate paths in the routing steps and hence is able to find more lightpaths than MmQ, which uses a single shortest path. Although K-SP-Q is impairment-aware, it only performs a QoT check at the end of the RWA process and does not incorporate physical layer information within the routing decision, leading to higher blocking rate. By increasing the amount of monitor deployment, the MCP routing engine finds routes that compensate for the inaccuracy of the QoT estimation, such that the blocking rate decreases.

In Fig. 3 we report the number of wavelengths needed to achieve 0% blocking rate for a given load, a metric of high interest to network designers. As the amount of monitoring equipment increases, "Rahyab" achieves 0% blocking rate with fewer wavelengths. MmQ, even assuming full monitoring, requires more wavelengths to accomodate the traffic than "Rahyab" variants. We do not show results for K-SP-Q as it is outperformed by MmQ.

Last, in Fig. 4, we report the maximum admissible load to achieve a blocking rate of 1%, when the amount of monitoring equipment varies. With MmQ, monitoring deployment is only accounted for in the QoT condition via a varying Q_{th}, i.e. $Q_{th} = 15.5$ dB for full monitoring deployment and $Q_{th} = 16.5$ dB for no monitoring deployment. "Rahyab" integrates monitoring deployment within the RWA decision and so benefits from the additional monitoring deployment better than MmQ, as can be seen with the increasing gap between the MmQ and "Rahyab" plots.

In summary, we presented a technique to account for QoT estimation uncertainty through the presence of monitors in transparent optical networks. This uncertainty metric was then used in an MCP framework, which is in turn embedded within a novel IA-RWA algorithm ("Rahyab"). We showed that "Rahyab" was able to accommodate more traffic or use less resources than state-of-the-art yet inaccuracy-unaware IA-RWA algorithms.

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4. References

[1] S. Azodolmolky et al., "A Survey on physical layer impairment aware routing and wavelength assignment algorithms in optical networks," Elsevier Computer Networks, **53**, 926–944 (2009).

[2] T. Zami et al., "The relevant impact of the physical parameters uncertainties when dimensioning an optical core transparent network," Proc. ECOC, Sep. 2008.

[3] P. Khadavi et al., "Multi-constraint QoS routing using a new single mixed metric," Elsevier Journal of Network and Computer Applications, **31**, 656–676 (2008).

[4] Y. Pointurier et al., "Cross-layer adaptive routing and wavelength assignment in all-optical networks," JSAC, **26**, 32–44 (2008).

[5] X. Yang et al., "Survivable lightpath provisioning in WDM mesh networks under shared path protection and signal quality constraints," JLT, **23**, 1556–1567 (2005).

[6] B. Ramamurthy et al., "Impact of Transmission Impairments on the Teletraffic Performance of Wavelength-Routed Optical Networks", JLT, **10**, 1713–1723 (1999).