A Novel Impairment Aware RWA Algorithm With Consideration of QoT Estimation Inaccuracy

Siamak Azodolmolky, Yvan Pointurier, Marianna Angelou, Davide Careglio, Josep Solé-Pareta, and Ioannis Tomkos

***Abstract*—In all-optical networks the physical layer impairments accumulate along a lightpath and also vary dynamically, and a number of impairment aware routing and wavelength assignment (IA-RWA) techniques have been proposed in order to mitigate the physical layer impairments and find lightpaths that meet a required quality of transmission (QoT) constraint predefined by the network operator. However, in order to compute lightpaths, IA-RWAs typically rely on analytical models, which cannot be guaranteed to be fully accurate, and hence acceptance of lightpaths with poor QoT or rejection of lightpaths with acceptable QoT may ensue. We present a novel IA-RWA algorithm that not only considers the impact of physical impairments on RWA decisions, but also, for the first time, accounts for inaccuracy of the QoT estimators. The performance of our algorithm is compared with algorithms selected from the recent literature. All algorithms are evaluated through simulations in a realistic scenario. Our proposed novel algorithm outperforms the selected algorithms in terms of blocking rate and also the amount of required resources for achieving a very low (i.e., 5×10^{-6}) blocking rate under similar assumptions. In addition we show that accounting for QoT estimation inaccuracy changes the performance of the proposed IA-RWA substantially, and hence that the QoT estimator inaccuracy is an important design parameter in transparent optical networking.**

***Index Terms*—Estimation inaccuracy; Impairment aware RWA; Physical layer impairments; Quality of transmission.**

I. Introduction

Next generation optical networks are evolving from opaque to optical-bypass (translucent) and eventually to transparent (all-optical) networks [1,2]. The transparency in next generation optical networks enables signals to propagate from source to destination purely in the optical domain, eliminating the current expensive electronic regenerators. This evolution paves the way for the construction of the required infrastructure for emerging data-intensive applications in a cost-effective manner [3].

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Despite those advantages, transparency in all-optical networks also introduces new issues in relation to the lack of electrical conversion as well as the still immature all-optical regeneration (e.g., 2R, 3R) technology. Since the optical signals go directly through all-optical nodes (instead of costly electrical regenerators), physical layer impairments accumulate along a lightpath and also vary dynamically with the network state or configuration, potentially causing the signals' quality of transmission (QoT), measured for instance in terms of the bit-error rate (BER), to drop beyond a predefined threshold. One way to mitigate physical impairments at network operation time is to use network-layer mechanisms, such as online routing and wavelength assignment (RWA) algorithms, to assign lightpaths (a lightpath is the combination of a route and a wavelength) accounting for the physical layer parameters, leading to the design of impairment aware routing and wavelength assignment (IA-RWA) algorithms, which have recently received a lot of attention from the research community [4].

One of the key building blocks in IA-RWA algorithms is a *QoT estimator*, which is a combination of theoretical models and/or interpolations of measurements, typically performed offline (in the lab, before the networks are deployed), but also possibly online. A practical QoT estimator should be fast to ensure that lightpaths can be established in real time. In addition, models by nature cannot capture all effects actually present in physical systems, resulting in QoT estimation inaccuracies. Inaccuracies are inevitable yet undesirable for two reasons: on the one hand, if the QoT of a candidate lightpath is estimated as acceptable while it is not, then a lightpath is established when it should not be. Eventually a monitor (such as a BER monitor integrated in the receiver) will catch the problem and the lightpath will be torn down and re-establishment will be requested, wasting resources used by the failed lightpath, and time. On the other hand, if the QoT of a candidate lightpath is estimated as unacceptable when the QoT is actually acceptable, then the IA-RWA algorithm will have to seek a new candidate for the lightpath, likely less optimal (e.g., consuming more resources) than the first candidate, hence again wasting resources and time. A practical IA-RWA algorithm should mitigate the inaccuracies due to QoT estimation in order to eliminate the occurrence of both cases to the maximum possible extent. Note that the problem of incorporating QoT estimation inaccuracies in the dimensioning of transparent optical networks was tackled in [5], where the authors studied the amount of regeneration devices needed to compensate for the additional QoT margin incurred by the inaccuracy of a QoT (Q factor) estimator; in [5] the problem of the impact of the RWA technique on the network dimensioning was left out. In this paper we propose to address such inaccuracies directly within the decision steps of the IA-RWA algorithm in order to mitigate them and eliminate the occurrences of both cases described above to the maximum possible extent.

In this work, we present a novel IA-RWA algorithm that considers the availability of optical impairment monitoring (OIM) or optical performance monitoring (OPM) [6] equipment to alleviate the inaccuracy of the QoT estimations. Such monitoring equipment can be deployed at the ends of the selected unidirectional fiber links to monitor the impairment or performance of the lightpaths, which are terminating at the ends of those links. However, the optimum monitor deployment is not the topic of this work. Assuming a given deployment, monitor equipment availability is mapped to QoT accuracy and is taken into account within a multi-constraint framework as a new constraint (the other constraint being a traditional QoT-related one), at the routing step of a proposed RWA heuristic. Doing so ensures that routes where monitors are available are preferred over routes with less monitoring capability, consequently increasing the accuracy of the QoT estimator and reducing the aforementioned issues associated with inaccurate QoT estimators. We show that our novel heuristic algorithm, which we call "online Rahyab,[1]" outperforms state-of-the-art IA-RWA algorithms under the same assumptions for common metrics such as blocking rate and resource utilization. The main contribution of this work is the multi-constraint framework to account for the inaccuracies of the QoT estimations and its integration in an IA-RWA algorithm that considers multiple paths for its routing decisions.

This paper is organized as follows. After this introduction, in Section II a physical layer performance evaluator (i.e., QoT estimator or "Q-Tool") is introduced. State-of-the-art online IA-RWA algorithms, against which our novel IA-RWA is evaluated, are summarized in Section III. Our novel online IA-RWA algorithm is presented in Section IV. Section V covers the assumptions, simulations parameters and results of our comparative studies. Conclusions are drawn in Section VI.

II. Physical Layer Performance Evaluation

In the context of transparent optical networks, impairments can be categorized into "static" and "dynamic" impairments. Static impairments are topology-dependent: they do not depend on the routing state of the network. In particular, we account for the following static impairments in this work: amplifier spontaneous emission (ASE) noise, filter concatenation, and polarization mode dispersion (PMD). Dynamic impairments depend on the presence and characteristics of other lightpaths established in the network. We account for the following dynamic impairments in this work: node crosstalk, originating from signal leaks at nodes, and nonlinear effects: cross phase modulation and four wave mixing (XPM, FWM).

[1] Rahyab means "path finder" in Persian.

A. QoT Estimator (Q-Tool)

To assess the QoT of a lightpath, we use a "Q-Tool," which is able to compute the so-called "Q factor" for a lightpath given the network topology, physical characteristics, and network state (i.e., what lightpaths are already present in the network). The Q factor for a lightpath is a QoT indicator that is related to the signal's BER using, for an on–off modulated signal,

$$\mathrm{BER} = \frac{1}{2}\mathrm{erfc}\left(\frac{Q}{\sqrt{2}}\right), \tag{1}$$

where the Q factor is defined as [7]

$$Q = \frac{P_1 - P_0}{\sigma_1 + \sigma_0}. \tag{2}$$

In Eq. (2), P_1 and P_0 are the means of the distributions (assumed to be Gaussian) of the received samples corresponding to the sent "1" and "0" bits, and σ_1 and σ_0 are the respective standard deviations. In the case of systems with intersymbol interference (ISI), the BER is dominated by those symbols that close the eye most, rather than the average power difference $P_1 - P_0$ [8]; hence, calling the eye opening after transmission P_{op}, the Q-Tool actually computes the following estimate:

$$\hat{Q} = \delta_{\mathrm{PMD}} \frac{P_{op}}{\sigma_1 + \sigma_0}. \tag{3}$$

As suggested in [9], we model filter concatenation impairment as a penalty on the eye opening, yielding the eye opening P_{op}. The PMD effect is modeled as a penalty on the Q factor as in [10] through the multiplicative factor δ_{PMD}. Other impairments are accounted for through noise variances. In particular let

$$\sigma_1^2 = \sigma_{1,\mathrm{ASE}}^2 + \sigma_{1,\mathrm{XT}}^2 + \sigma_{1,\mathrm{XPM}}^2 + \sigma_{\mathrm{FWM}}^2, \tag{4}$$

$$\sigma_0^2 = \sigma_{0,\mathrm{ASE}}^2 + \sigma_{0,\mathrm{XT}}^2. \tag{5}$$

ASE noise is modeled as a noise variance according to [7] and contributes to both σ_1 and σ_0 via $\sigma_{1,\mathrm{ASE}}^2$ and $\sigma_{0,\mathrm{ASE}}^2$, respectively. Since P_{op}, $\sigma_{1,\mathrm{ASE}}$ and $\sigma_{0,\mathrm{ASE}}$ only depend on the network topology and physical parameters (as does δ_{PMD}), they can be precomputed for fast Q factor estimation. We also model node crosstalk as a noise variance affecting "1" and "0" bits according to [11] via the quantities $\sigma_{1,\mathrm{XT}}^2$ and $\sigma_{0,\mathrm{XT}}^2$. The XPM effect is modeled according to [12] and accounted for within σ_1^2 via $\sigma_{1,\mathrm{XPM}}^2$. Similarly the FWM effect is modeled according to [13,14] and is accounted for within σ_1^2 via σ_{FWM}^2. Since node crosstalk, XPM and FWM are dynamic effects that depend on the network state, $\sigma_{1,\mathrm{XT}}^2$, $\sigma_{0,\mathrm{XT}}^2$, $\sigma_{1,\mathrm{XPM}}^2$ and σ_{FWM}^2 have to be computed online by the Q factor estimator. We refer the reader to [7,9–14] for additional details about the modeling of each physical impairment.

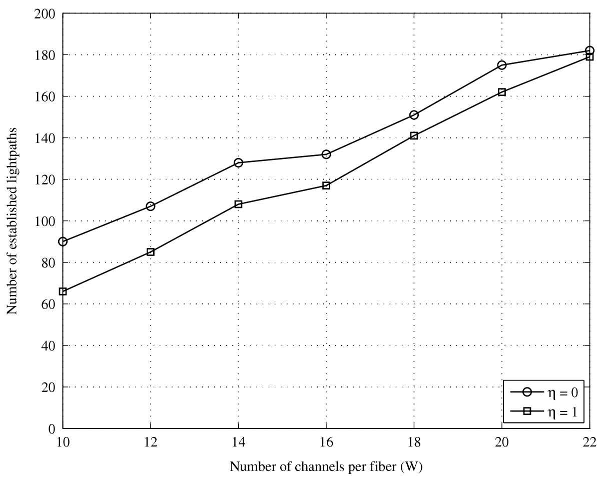

Fig. 1. Number of established lightpaths until the occurrence of the first QoT blocking as a function of available wavelengths per fiber, assuming $Q_{EM} = 0.5$ dB and for two extreme values of η.

B. Inaccuracy of the Q-Tool

Practical QoT estimators including our Q-Tool are combinations of analytical models and/or interpolations of measurements and simulations. For instance, in [15] the authors propose a method to measure more accurately the optical signal to noise ratio (OSNR) on transmission lines at the expense of the deployment of additional power monitors. However, practical QoT estimators should be fast in order to support quick lightpath establishment. This is particularly required in highly dynamic transparent optical networks. As mentioned above, the errors resulting from incorrect QoT estimation have a direct impact on lightpath establishment decisions, yet physical models are by nature imperfect and optimization for speed is further detrimental to their intrinsic accuracy. Utilizing the optical performance and/or impairment monitoring devices is a good approach to bypass some analytical models and alleviate the inaccuracy of the QoT estimation process. For instance, a Q factor monitor can simply replace the whole Q-Tool and provide the precise Q factor value of a lightpath. We formalize here the trade-off between availability of monitoring information and monitoring accuracy.

In our framework a lightpath with estimated Q factor $\hat{Q}$ by the Q-Tool is established if and only if $\hat{Q}$ is larger than a given threshold Q_{th} (e.g., $Q_{th} = 15.5$ dB to achieve BER $= 10^{-9}$ without forward error correction (FEC)), to which we add a margin ηQ_{EM} $(0 \le \eta \le 1)$:

$$\hat{Q} > Q_{th} + \eta Q_{EM}. \tag{6}$$

In Eq. (6), the Q_{EM} parameter is the maximum error (inaccuracy) that the Q-Tool estimator can introduce, and η is a factor that depends on the availability of the additional monitoring information.

As an illustrative example, assume that a network operator is running a network and injects traffic until it sustains a first call blocking. This call blocking can be due to either lack of resources (wavelength blocking) or QoT insufficiency (QoT blocking). Note that in the following experiment, the available channels per fiber are selected in such a way that QoT blocking is the only source of blocking of demands. This is done for a 14-node national network similar to the one operated by Deutsche Telekom (see Section V for full details). The number of established lightpaths is given for $Q_{th} = 15.5$ dB, $Q_{EM} = 0.5$ dB, and for the two extreme values of η: $\eta = 0$, corresponding to the case where we have full confidence in the Q factor estimator and assume that it returns the true Q factor of a lightpath (possibly because some monitors are deployed, which greatly improve the Q-Tool accuracy), and $\eta = 1$, corresponding to the case with maximum inaccuracy of the Q-Tool. It is seen in Fig. 1 that a higher confidence in the estimate of Q or, alternatively, a lower value of η, permits us to postpone the point in time when the first blocking occurs; for a system with 10 channels we can accommodate 40% more lightpaths if we have high confidence in the Q estimates ($\eta = 0$), compared with the case where we do not ($\eta = 1$). However this difference is reduced to 2% when the number of channels per fiber is increased to 22. The reason for this reduction is that the availability of more wavelengths increases the chance of finding a lightpath that satisfies the (higher) required threshold. This framework enables us to place some constraint on the adaptive error factor η in order to force the routing engine to find paths with more accurate QoT estimation. We observe that even a small inaccuracy in QoT estimation (e.g., 0.5 dB) changes the performance of the call admission procedure. In the example above, η is set to a fixed value; however, it is clear from the example that gains in call admission performance are expected if η can be lowered. We propose to account for OIM/OPM availability information dynamically, on a per-route basis, in order to compute the true value of η for each lightpath, and hence to reduce the QoT blockings due to too high margin on $\hat{Q}$ whenever that is possible, using an appropriate, novel IA-RWA algorithm. Before we do so, we review some of the state-of-the-art IA-RWA algorithms proposed in the literature.

III. Online IA-RWA Algorithms

As we mentioned previously, much effort has been devoted to the topic of IA-RWA in the past few years; in [4] we proposed a comprehensive survey of such algorithms, and here we simply use the conclusions of [4] to choose suitable candidates to compare our new IA-RWA algorithm with. Note that no IA-RWA so far has accounted for Q factor estimation inaccuracy, and hence the algorithms presented here assume a constant margin ηQ_{EM}. The following two algorithms were selected because of their performance in terms of average blocking rate in fully transparent optical networks.

The K-SP-Q algorithm is described in [16]. This algorithm selects the shortest available route among the K routes between each source and destination pair, which are precomputed as the K shortest paths; the first fit wavelength assignment scheme is utilized; and finally this algorithm checks the QoT value.

The MmQ (Max Min Q factor) algorithm is described in [17]. In the MmQ algorithm for each wavelength a route from source to destination is computed subject to the wavelength continuity constraint. Then, for each of the computed lightpaths, the QoT values of that candidate lightpath and already established lightpaths are computed. Lightpaths with a value of Q lower than a given threshold, or lightpaths that interfere with other lightpaths so as to produce a value of Q for them lower than the threshold, are discarded. From the list of previously computed lightpaths that are not discarded, the one with the highest QoT value is finally selected. In addition to low blocking, the algorithm has some desirable properties such as high fairness between short and long lightpaths.

In the next section we propose our novel online IA-RWA algorithm.

IV. Online Rahyab

The main idea behind the online Rahyab algorithm is to design a multi-constraint IA-RWA algorithm that considers QoT accuracy through optical monitor (i.e., OIM/OPM) availability information in routing decisions, in order to alleviate the inaccuracy of the QoT estimator (here, Q-Tool). Online Rahyab selects the routes in such a way as to compensate for the inaccuracy of the QoT estimation (by selecting routes that are equipped with OIM/OPM devices) and therefore to increase the chance of finding a lightpath with an overall acceptable QoT metric. This will pave the way for lower QoT blocking. Our multi-constraint IA-RWA maps several constraints, including QoT itself, and QoT inaccuracy, to a single metric, using a technique proposed in a more general context [18], which we detail in Subsection IV.A; we then use this metric in a novel IA-RWA algorithm, which we present in Subsection IV.B.

A. Multi-constraint Paths

Multi-constraint path (MCP) computation algorithms have been used for the quality of service (QoS) routing problem in general wired networks [19–22], but to the best of our knowledge have never been applied for solving the online IA-RWA problem in optical networks. Finding paths subject to two or more cost parameters/constraints is an NP-complete (nondeterministic polynomial time) problem in the general case [19]. As a result, most proposed algorithms concentrate on solving the MCP problem with polynomial or pseudo-polynomial time heuristics. In particular, one technique consists in the reduction of the original MCP to a single-constraint path problem, using an appropriate mapping between the original multiple constraints and the single constraint effectively used in the routing step. This is the approach that we follow in this work. In particular, we use the same mapping as in [18] in our RWA algorithm. Before we describe the RWA algorithm itself, we present the multi- to single-constraint mapping used throughout this work.

The MCP problem can be formulated as follows. Consider a network topology $G = (V,E)$ with nodes V and edges E, a source node S and a destination node D. Also assume that each link $e \in E$ is characterized by M additive non-negative weights, $w_m(e), m = 1,2,\dots,M$. Given constraints $C_m, m = 1,2,\dots,M$, the MCP problem is to find a path p such that

$$\sum_{e\in p} w_m(e) < C_m; \quad m = 1,2,\dots,M. \tag{7}$$

In [18] the following mapping between the multiple edge costs $w_m(e)$ and a single-cost metric $\mathrm{SMM}_d(e)$ is introduced:

$$\mathrm{SMM}_d(e) = \mu_d(e)\left[\Delta_d(e)+\epsilon\right]; \quad 0 \le \epsilon \le 1, \tag{8}$$

where

$$\mu_d(e) = \frac{1}{M}\sum_{m=1}^{M}\left(\frac{w_m(e)}{C_m}\right)^d; \quad d \ge 1, \tag{9}$$

$$\Delta_d(e) = \sum_{m=1}^{M}\left[\left(\frac{w_m(e)}{C_m}\right)^d - \mu_d(e)\right]^2. \tag{10}$$

The single metric that we are going to use in our framework is defined in Eq. (8). This relation considers the impact of both mean and variance of the normalized weights (to the power d, which is a parameter) of the links in the single mixed metric (SMM). The contribution of the mean (as defined in Eq. (9)) with respect to the variance is controlled by ϵ, another parameter. This SMM or cost is shown in [18] to have desirable properties with respect to the MCP problem; in particular, for the 2-constraints problem ($M = 2$) it can be shown that the SMM can be used in conjunction with a standard shortest path algorithm to select paths that exactly satisfy the constraints (7); for problems with more constraints ($M > 2$), exact satisfaction (7) is not feasible, but can be performed with high probability using the SMM and a shortest path algorithm.

B. Description of Online Rahyab

The novelty of our approach and framework compared to the one reported in [18] is the exploitation of the single-cost metric for k-shortest path and/or diverse k-shortest path algorithms. Indeed, while in [18] the Dijkstra algorithm is modified to find a single path between source and destination, we are using here the MCP framework based on a single mixed metric for computing a set of multiple candidate paths between source and destination nodes, for any dynamic demand request. Furthermore, we can exploit this MCP engine for diverse routing (e.g., the Bhandari algorithm [23]) for protection purposes (e.g., $1+1$) or generic k-shortest path algorithms. In the online Rahyab algorithm we are considering two metrics as the link cost parameters $w_i(e)$: lightpath length and Q-Tool inaccuracy margin. Note that the framework can easily be extended to include various other constraints, such as, for instance, the energy consumption per link, to yield an energy efficient IA-RWA.

Lightpath lengths: Capping the length of a lightpath is a quick and easy way to disregard candidate lightpaths with poor QoT; indeed, considering only static impairments, i.e., impairments that do *not* depend on the network state—ASE noise, PMD and filter concatenation—one can compute the maximum length $L_{\max}$ of a lightpath such that the QoT constraint is met. Lightpaths longer than $L_{\max}$ are known for sure to have an unacceptable QoT; note that the converse does not hold, as lightpaths shorter than $L_{\max}$ may also have an unacceptable QoT when dynamic effects (XPM, FWM) are accounted for. The main idea here is to consider the static physical impairments inside the multi-constraint path computation engine in order to prune out paths that do not satisfy the minimum QoT requirements (as far as the static physical impairments are concerned). Hence, the first metric we consider here is the length, that is, $w_1(e) = \ell(e)$, where $\ell(e)$ is the length of link e, and the associated constraint is

$$\sum_{e \in p} \ell(e) < L_{\max}, \tag{11}$$

where $L_{\max}$ is a precomputed constant and p is a lightpath.

QoT estimator inaccuracy: The second metric we consider is the Q-Tool inaccuracy. Define the *optical monitor availability vector* as a binary vector that records whether a particular monitor is available on a unidirectional link or not, where each m_k is associated to the presence ($m_k = 1$) or absence ($m_k = 0$) of a monitor (for instance, OSNR monitor, PMD monitor, residual chromatic dispersion monitor, channel monitor, etc.) on a given link. In order to map the monitor availability vector of link e to a single value we define the function Θ as follows:

$$\Theta(e) = \sum_{k=1}^{n} \epsilon_k(e)(1 - m_k(e)). \tag{12}$$

In Eq. (12) the sum is indexed by the monitors and we assume that we can use n different monitors for each link e. The parameter ϵ_i determines the importance of the ith monitor. More specifically, 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 $\epsilon_i(e)$ as the contribution to the variance of $\hat{Q}$ due to the absence of monitor i on link e. We can then re-interpret the adaptive factor η for a lightpath p introduced in Eq. (6) as

$$\eta(p) = \frac{\sum_{e \in p} \Theta(e)}{\Theta_{\max}(p)}, \tag{13}$$

where $\sum_{e \in p} \Theta(e)$ is the variance of $\hat{Q}$ accounting for uncertainties stemming from the presence/absence of monitors on each link of the considered lightpath, and $\Theta_{\max}(p)$ is the maximum variance for the lightpath. This maximum uncertainty corresponds to the absence of monitors on a lightpath. The constraint corresponding to this QoT uncertainty metric is then

$$\eta(p) < \eta_{\max}, \tag{14}$$

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 path for a lightpath to be established.

We now describe the complete IA-RWA, "online Rahyab." In online Rahyab each link is associated with a single weight w_e, which mixes the two metrics "link length" and "QoT estimator uncertainty," using Eq. (8). Upon the arrival of a connection request between a source and a destination node, the current network topology is decomposed into W layers (wavelength planes), where W is the total number of channels in each fiber. For each wavelength plane, we compute a predefined number K of candidate paths from source to destination using a shortest path algorithm with the two metrics $w_1(e) = \ell(e)$ (length) and $w_2(e) = \Theta(e)$ (QoT estimator uncertainty). Therefore, the multi-constraint routing engine is exploited for finding paths (denoted by *candidate lightpaths*) that satisfy multiple constraints. Doing so separately for each wavelength ensures that the candidate lightpaths also conform to the wavelength continuity constraint. Once *candidate* lightpaths are determined, we construct another set of lightpaths, which we call the *usable* lightpaths: we temporarily add each candidate lightpath to the currently established lightpaths in the network and we compute the impact of this addition on the QoT of each lightpath already established. If all QoT values are above a certain threshold, the candidate lightpath under consideration will be moved to the *usable* lightpath set. In this step, we use the Q-Tool that considers all physical impairments as defined in Section II. The final step of our algorithm is to select the best usable lightpath. In order to find this lightpath, we select the lightpath that introduces the minimum impact on the currently established lightpaths (as suggested in [17]). We exploit the QoT estimator (i.e., Q-Tool) to compute the *QoT margin* of each candidate route (with respect to the minimum allowed Q factor) on the currently established lightpaths:

$$Q_{margin} = \min\left(\mathbf{Q} - Q_{th} - \hat{\eta} Q_{EM}\right). \tag{15}$$

The margin is computed by subtracting $Q_{th} + \hat{\eta} Q_{EM}$ from the Q factors of all active lightpaths (including the candidate lightpath) and finding the minimum value, as expressed in Eq. (15), where $\mathbf{Q}$ is a vector that includes the Q factors of all lightpaths established in the network and $\hat{\boldsymbol{\eta}}$ is a vector that includes the value for the inaccuracy factor (η) of each established lightpath using Eq. (13). The next step is to select a lightpath from the *usable* lightpath set. We consider a heuristic, by which the lightpath with the highest non-negative Q_{margin} is selected. In the case where the *usable* set is empty, the demand is blocked. The flow chart of the online Rahyab algorithm is depicted in Fig. 2.

V. Comparative Studies

In order to provide a fair comparison between the algorithms, we performed simulations with controlled and identical input parameters and an identical impairment estimation module (Q-Tool). The parameters and the set of experiments were chosen so as to obtain a broad range of results that would reveal the relative performance of the algorithms and their applicability under diverse scenarios. In addition to online Rahyab, we also evaluated the performance of the K-SP-Q and MmQ algorithms, which we described in Section III.

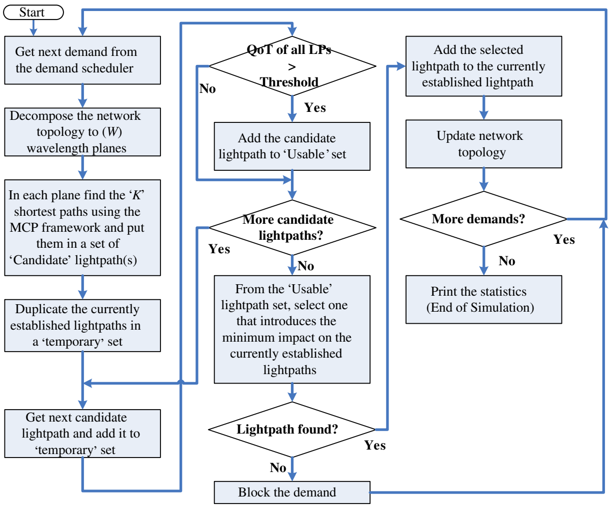

Fig. 2. (Color online) Flow diagram of online Rahyab.

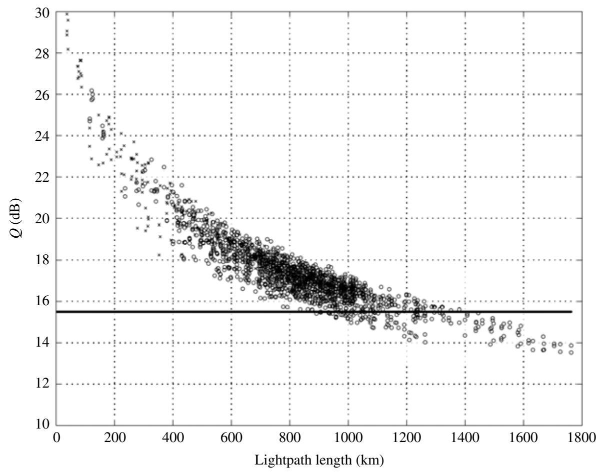

Fig. 3. Q-factor value versus lightpath length (Q_{th} = 15.5 dB).

A. Assumptions and Simulation Parameters

The network topology in our simulation studies, DTNet, was provided by Deutsche Telekom (DT) and is similar to the real national network operated by DT. This network has 14 nodes and 23 bidirectional links, with an average node degree of 3.29. The line rate in this network is assumed to be 10 Gbps. We assume a heterogeneous network topology in which the node and link architectures have different impacts and contributions on the physical layer impairments. We also assumed that pre-dispersion compensation of 400 ps/nm is performed in the links. The standard single mode fiber (SSMF) length in each span is set to 100 km, followed by a dispersion compensation fiber (DCF) that under-compensates the dispersion of the preceding SSMF by a value of 30 ps/nm/km. At the end of each link the accumulated dispersion is fully compensated. It was assumed that the SSMF fibers have a dispersion parameter of 17 ps/nm/km and attenuation of 0.25 dB/km. The DCF segments have a dispersion parameter of 80 ps/nm/km and an attenuation of 0.5 dB/km. The input power to the links is −4 dBm and 3 dBm per channel in the DCF and SSMF fibers, respectively. The channel spacing is set to 50 GHz. The noise figure of the amplifiers that compensate for the loss of the preceding fiber segment is set to NF ≈ 6 dB, with small variations. The signal-to-crosstalk ratio in nodes is set around −32 dB, with small variations in each node. The threshold value for computing the impact on Q factor (i.e., Q_{th}) is 15.5 dB, corresponding to BER = 10^{-9} without FEC.

In Fig. 3, we depict the Q factor value for all 10 shortest paths between all possible pairs of the nodes in the network, totaling 1820 lightpaths. Without considering the impact of other established lightpaths, the maximum optical reach is about 1500 km; hence we set $L_{\max}$ = 1500 km in the constraint (11). We also set $\eta_{\max}$ = 0.9 in constraint (14). $\eta_{\max}$ is a parameter and determines the maximum uncertainty that the network operator is willing to tolerate. The lower the value of this parameter, the higher the chance of finding a feasible lightpath (i.e., the lower the impact of QoT estimation inaccuracy).

Connection requests (dynamic demand set) are generated according to a Poisson process with rate λ (requests/time unit). The source and destination of a connection are uniformly chosen among the nodes of the network. The duration of a connection is given by an exponential random variable with average $1/\mu$. We varied the ratio λ/μ which measures, in Erlangs, the total offered load to the network. Connection requests arrive one by one and should be served upon their arrival. This means that the algorithm cannot wait to collect more than one connection and serve them jointly. In each experiment, 1000 connections per each pair of nodes were created and served. In practical applications, the number of available channels per fiber (W) is in the range of 80–160 channels. However, the focus of this work is to address the inaccuracy of the QoT estimation. The reported results in this work are for a proof of concept and we do not expect a major difference in results if the value of W is increased.

In the K-SP-Q algorithm, the value of K is set to 5. In the online Rahyab algorithm, we set the values of d and ϵ to 1 and 0.5, respectively, in order to compute the single mixed cost for links. As indicated in [18], these parameters are good choices for the performance of our MCP engine. The Rahyab algorithm sets the value of K to 5 for computing candidate routes.

B. Results

In order to evaluate the performance of different algorithms we considered the following performance metrics: the blocking rate for each demand set, which is the ratio of the number of blocked lightpath requests over the total number of requested lightpaths (we report this metric for different values of both load and also number of channels per link), the number of required wavelengths in order to achieve a blocking rate lower than 5×10^{-6} for a given demand set, and the admissible load to the network to achieve 1% blocking rate for different monitor deployment scenarios. These metrics are good indicators for network designers in order to perform network planning and dimensioning.

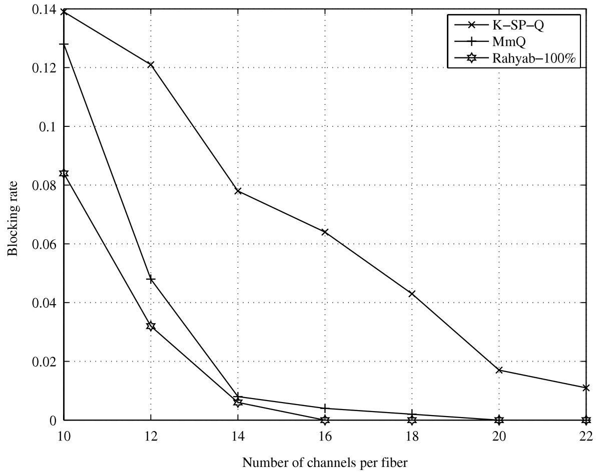

Fig. 4. Blocking rate versus number of channels per link, $Load = 100$ Erlangs.

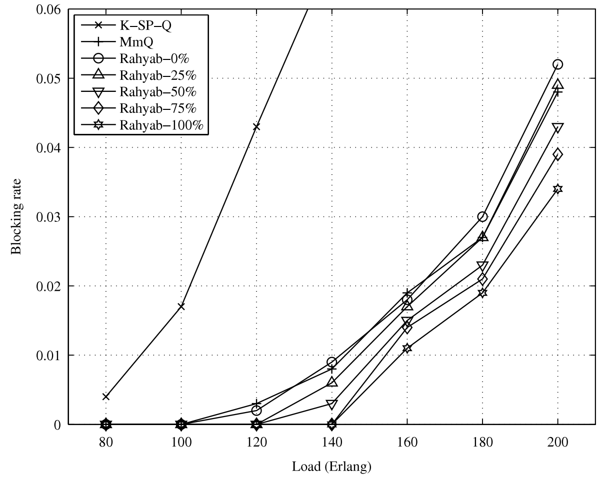

Fig. 6. Blocking rate versus load ($W = 20$).

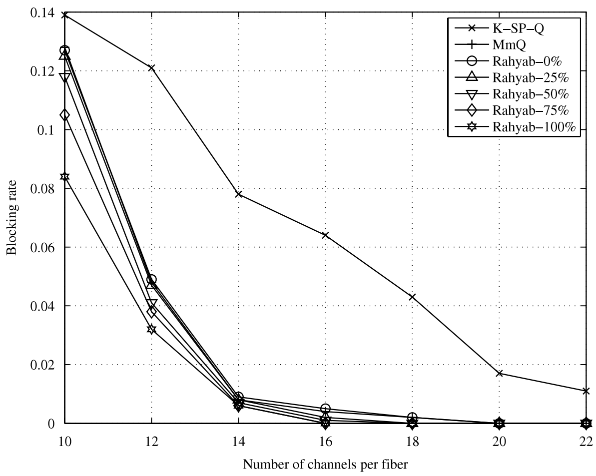

Fig. 5. Blocking rate versus number of channels per link, $Load = 100$ Erlangs.

Figure 4 depicts the performance of K-SP-Q, MmQ and our proposed online Rahyab algorithm ("Rahyab-100%"). In our experiments we evaluated the performance of the algorithms assuming that QoT blocking is possible, and as a result we are interested in minimizing its occurrence. Note that there is no QoT inaccuracy consideration in K-SP-Q and MmQ, and therefore their performance should be compared with Rahyab with full monitor deployment ("Rahyab-100%") that completely removes the inaccuracy of QoT estimation. The results are presented as a function of the number of channels per fiber, for a fixed network load (100 Erlangs).

In order to reveal the impact of the monitors on the performance of the online Rahyab algorithm, we varied the deployment rate of monitors in the network between 0% and 100%. The results are depicted in Fig. 5. We also included the performance of the MmQ and K-SP-Q algorithms for comparison purposes. The five variations of the Rahyab algorithm are denoted as Rahyab-0% to Rahyab-100%, which correspond respectively to no or full OIM/OPM deployment in the network. For the case of 0% monitor deployment, we have assumed that $Q_{EM} = 1$ dB, as also considered in [5]. We can observe that when there is no inaccuracy in QoT estimation (100% monitor deployment), the online Rahyab algorithm performs better than all other algorithms. Besides, by increasing the number of channels per fiber the blocking rate is decreased, since the chance of finding a route and available wavelength that satisfy the required QoT threshold increases. The performance of the MmQ algorithm that does not consider the inaccuracy of QoT estimation is almost similar to the performance of the Rahyab algorithm without any monitor deployment, i.e., 0% monitor deployment. The reason why the online Rahyab algorithm performs better than MmQ is mainly due to the availability of additional route options in online Rahyab compared to single shortest path in the MmQ algorithm. The K-SP-Q algorithm does not perform better, mainly due to the inability to properly incorporate the impact of physical impairments in its routing decisions.

By increasing the amount of OIM/OPM monitoring equipment, the online Rahyab MCP routing engine finds routes that compensate for the inaccuracy of the QoT estimation, which is why the blocking rate decreases when the optical monitor deployment rate increases. However, the difference between various deployment scenarios is more pronounced for lower numbers of channels per fiber. Indeed, by increasing the number of channels, finding a proper route and available wavelength that satisfies the QoT requirement becomes easier. When the number of channels per link is set to 10, Rahyab-100% (with support of full OIM/OPM deployment) performs 51% better than the same algorithm in the absence of any OIM/OPM monitor deployment (i.e., Rahyab-0%).

Figure 6 depicts the performance of the selected algorithms for different values of the network load and a fixed number of channels per link (i.e., $W = 20$). The increase of the network load, as expected, deteriorates the performance of all algorithms, just as the performance of the algorithms deteriorates when the number of wavelengths is decreased. Among the studied algorithms, the Rahyab and MmQ perform better than the K-SP-Q algorithm. In this figure we included five variations of the Rahyab algorithm to also consider the impact of OIM/OPM deployment. By increasing the number

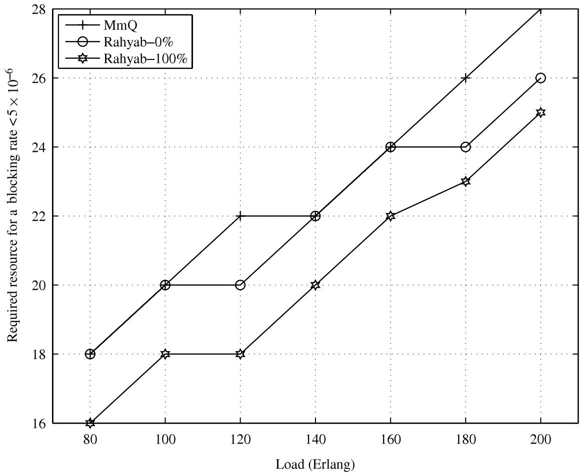

Fig. 7. Number of required W for a blocking rate less than 5×10^{-6} versus load.

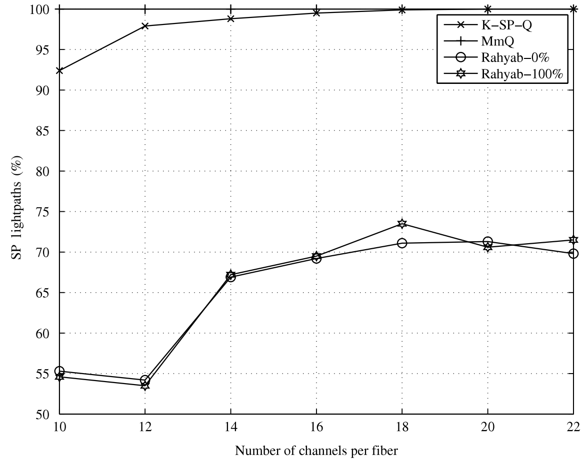

Fig. 8. Shortest path established lightpaths versus number of available channels per fiber.

of deployed monitors, the Rahyab MCP engine finds routes with more available monitors that lead to lower inaccuracy of QoT estimation. Note that we only consider the inaccuracy of QoT estimation for the online Rahyab algorithm (except Rahyab-100%), and the other algorithms exploit a Q-Tool without any inaccuracy (i.e., $Q_{EM} = 0$ dB). At the maximum load (200 Erlangs), the online Rahyab with full monitor deployment performs 53% better than online Rahyab without any monitor deployment.

By increasing the percentage of the OIM/OPM deployment in the network, the Rahyab MCP engine exploits the routes with more available monitors and reduces QoT inaccuracy, and therefore the number of lightpaths that are rejected due to the inaccuracy of the QoT estimation is decreased. We also observe that the MmQ algorithm that does not consider the inaccuracy of QoT estimation performs similar to the Rahyab without any OIM/OPM monitor deployment (Rahyab-0%).

The other performance metric of our comparative study is the number of required channels per link in order to achieve a blocking rate less than 5×10^{-6} for each traffic load. For this performance metric we have selected MmQ and two variations of the Rahyab algorithm. As before the MmQ algorithm does not consider the inaccuracy of the QoT estimation. As depicted in Fig. 7, online Rahyab—which utilizes the monitor availability information—is able to accommodate more traffic compared with MmQ and Rahyab without OIM/OPM deployment, for a given number of channels per link.

Figure 8 depicts the percentage of the lightpaths that are established along the shortest path between the source and destination nodes. Since the Rahyab MCP routing engine computes multiple candidate routes, it is able to find many possible candidates, and when the number of available wavelengths is few, more diverse routes are selected that eventually fulfill the QoT requirement. When the number of channels increases, the percentage of the lightpaths that are along the shortest paths also increases. MmQ only tries the shortest path routes. K-SP-Q also establishes most of the lightpaths along the shortest path. We have to note that this percentage only includes the lightpaths that were feasible and, since the blocking rate in K-SP-Q is higher than for the other selected algorithms, it has not been able to find other candidate paths. The MmQ algorithm, however, utilizes an adaptive wavelength assignment and therefore finds the shortest path that does not introduce any impact on the currently established lightpaths. This result indicates that it is possible to find routes that are not necessarily the shortest path, while achieving the required QoT.

In Fig. 9, we report the maximum admissible load to achieve a blocking rate of 1%, when the amount of monitoring equipment deployment 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 therefore benefits from the additional monitoring deployment more than MmQ, as can be seen from the increasing gap between the MmQ and Rahyab curves. When there is no monitor deployment in the network, the gap amounts to only 6%, while by increasing the rate of monitor deployment the performance of the Rahyab algorithm becomes better than the MmQ algorithm by 11%. We have also enhanced the MmQ algorithm to consider the monitor deployment rate in its RWA decisions in the same way that Rahyab considers it, and, as can be observed, the "enhanced" MmQ algorithm performs better than the MmQ algorithm. However, since the MmQ algorithm only computes a single path between the source and destination, its performance still remains lower than the Rahyab algorithm.

In order to evaluate the time complexity and scalability of the algorithms, we defined the relative average running time performance metric. This metric is the ratio of the average running time of a given algorithm for a given load (per connection establishment) over the average running time of the same algorithm for the reference load (i.e., Load = 200 Erlangs). This relative metric removes the dependence of the running time of an algorithm on the performance of a particular hardware/software platform. Figure 10 depicts the running time performance of the K-SP-Q, MmQ and Rahyab (with 100% monitor deployment) algorithms. The absolute running times of K-SP-Q, MmQ and Rahyab were 48.43, 253.23, and 552.86 s, respectively, for the reference

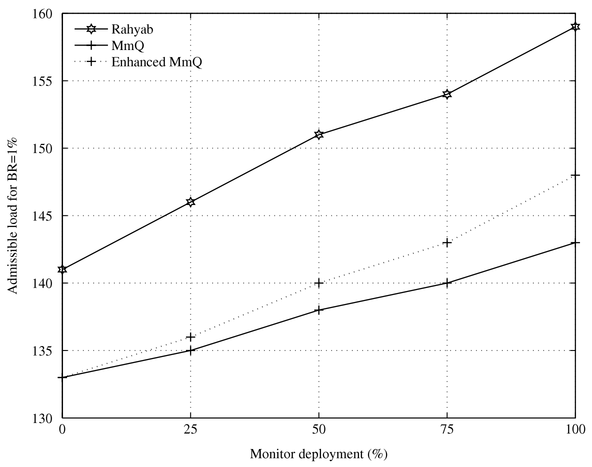

Fig. 9. Admissible load to achieve 1% blocking rate.

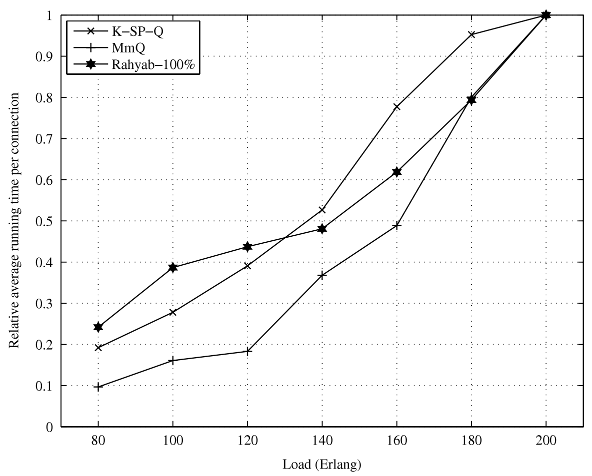

Fig. 10. Relative average running time per connection for the K-SP-Q, MmQ and Rahyab algorithms.

load. The MmQ and Rahyab algorithms intensively use the QoT estimator. Given the complexity of the analytical models inside the Q-Tool, the running time of Rahyab is much higher than the other selected algorithms. For a single unprotected demand, the maximum number of Q-Tool invocations is equal to the number of candidate paths in each wavelength layer (i.e., $k \times W$, in which k is the number of candidate paths and W is the number of wavelengths per link). In this work, we have used a software-based Q-Tool, which is not optimized for QoT computation. In practical applications, it is possible to utilize the hardware (e.g., FPGA) accelerated QoT estimator to achieve better computation time.

VI. Conclusions

We have presented a novel online IA-RWA algorithm, called "online Rahyab," that considers the availability of the OIM/OPM monitors in the network within the routing and wavelength assignment process. Indeed, a fundamental aspect in order for an IA-RWA strategy to be actually implemented is to utilize OIM/OPM for evaluation of signal quality. In addition to the exploitation of monitoring information in IA-RWA engines, it is also useful to incorporate the availability of OIM/OPM monitors in QoT estimations. We showed that for a system with 10 channels per fiber, we can accommodate 40% more lightpaths if we have high confidence in the Q estimations, compared with the case where we do not have high accuracy. We compared the performance of our proposed algorithm with two other algorithms that we have selected from state-of-the-art IA-RWA algorithms. Our simulation results indicate that utilizing the optical monitors in the network can improve the performance of the IA-RWA algorithms by roughly more than 50% for high traffic load or limited number of channels. We demonstrated that the admissible load for a given blocking rate is 11% higher than the one which is allocated by an algorithm that does not consider the OIM/OPM deployment in the network. We have also demonstrated that, due to the important impact of QoT estimator inaccuracies on network dimensioning (here, in terms of blocking rate), RWA algorithms need to incorporate those inaccuracies in order to appropriately reflect the actual behavior of monitored transparent optical networks. The online Rahyab algorithm can be considered as a building block of an impairment aware control plane deployment. The control plane integration schemes (i.e., centralized or distributed) and related issues (e.g., scheduling and advertisement of monitoring information) are beyond the scope of this work and will be investigated in future works.

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