

Reinforcement Learning Based Routing in All-Optical Networks with Physical Impairments

Yvan Pointurier and Fariba Heidari

Electrical and Computer Engineering
McGill University, Montreal, QC, Canada

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IEEE BROADNETS: Optical Cross-Layer Design

Reinforcement
Learning
Based Routing
in All-Optical
Networks with
Physical
Impairments

Outline

Introduction

Lightpath
model

Reinforcement
learning
routing

Simulations

Conclusions
and future
work

- 1 Introduction
- 2 Lightpath model
- 3 Reinforcement learning routing
- 4 Simulations
- 5 Conclusions and future work

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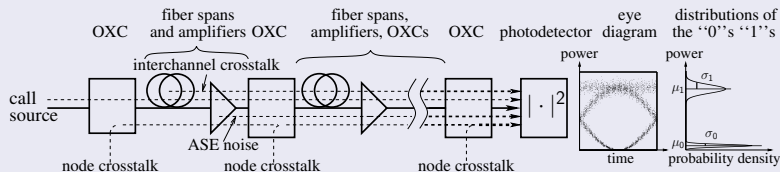
Simulations

Conclusions
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work

- Current high-speed optical networks
 - Bottleneck due to electrical conversions
- Features of all-optical networks
 - Circuit switched → lightpaths
 - Flexibility (traffic engineering), speed, cost
- New issues arise with all-optical networks
 - Optical regeneration currently unavailable
 - Signal impairments are transmitted over extremely long paths without any regeneration
 - Physical layer cannot be considered as perfect
⇒ Bit-Error Rate (BER)

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$$Q = \frac{\mu_1 - \mu_0}{\sigma_0 + \sigma_1}, \text{BER} = \frac{1}{2} \text{erfc}\left(Q/\sqrt{2}\right)$$

- ISI (chromatic dispersion, SPM)
- Amplifier (ASE) noise
- Interchannel crosstalk (XPM, FWM)
- Node crosstalk (optical leaks within nodes)
- BER depends on all these effects (and more)

Offline Routing

- Fixed Routing
- Time Dependent Routing

Online Routing

- State Dependent Routing
- Event Dependent Routing
 - Reinforcement learning

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Specificities of RWA in all-optical networks:

- Wavelength continuity constraint
- QoS constraint \Rightarrow cross-layer design
- Distributed algorithms are desirable
- Design a reinforcement learning algorithm
 - Account for physical impairments
 - Distributed
 - Make routing decisions based on network feedback

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Setup

- Alternate routing, wavelength assignment fixed (first-fit)
- Routes between s and d : $\{R_i^{s,d}\}$
- Load Sharing Factor ($P_i^{s,d}$): probability of selecting $R_i^{s,d}$

Algorithm description

Upon receiving of a new lightpath establishment request between s and d :

- Select one route $R_i^{s,d}$ at random using $\{P_i^{s,d}\}$
- Check all wavelengths in turn for the wavelength continuity and the QoS constraint
 - Accept call on first wavelength that meets all constraints
- Update $\{P_i^{s,d}\}$ using reinforcement learning techniques and Accept/Reject information

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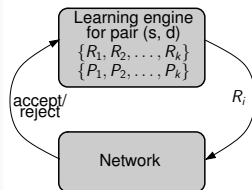
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Need an updating scheme suitable for

- Incomplete information about the network
- Learn routing policy via trial and error

Learning Automata

- Linear Reward \mathcal{E} -Penalty (LR \mathcal{E} P)
 - Linearly increase P_i when lightpath is accepted on route R_i
 - Linearly decrease P_i when lightpath is rejected on route R_i
- penalty param. \ll reward param.
- Performs well in non-stationary environments
- Does not get stuck in absorbing states
- Suboptimal

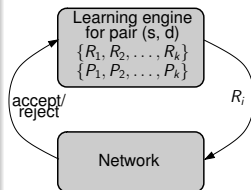


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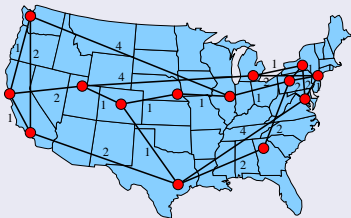
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NSF topology



Parameters

Description	Value
Span length	70 km
Fiber type	SMF
Nonlinearities	2.2 (W/m)^{-1}
Dispersion	100% post
Pulse shape	NRZ
Peak power	2 mW
Bit rate	10 Gbps
Max BER	10^{-9}
# wavelengths	8
# alt. routes	4

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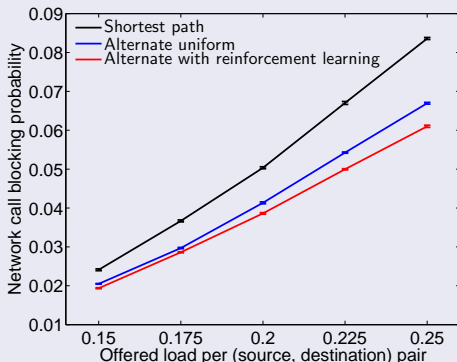
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- Compare with plain shortest path and random route choice
- Blocking rates are lowered by $\approx 10\%$ at higher loads

Conclusions

- Proof of concept
- Blocking rates can be lowered using Reinforcement Learning
- The routing technique is completely distributed

Future work

- Combined routing and wavelength assignment
- Questions ?