Recursive Bayesian Traffic Prediction
for Performance Improvement in OBS Networks

by

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Abstract

This thesis deals with traffic prediction in Optical Burst Switched (OBS) networks with self-similar traffic, i.e., traffic with long-range dependence (LRD) properties. Aggregated traffic in high speed optical networks exhibits LRD properties. OBS is a recent promising optical network technology to facilitate IP-Over-WDM (Internet Protocol Over Wavelength Division Multiplexing). To improve the quality of service (QoS) in OBS transmission networks, traffic prediction is required for dynamic resource reservation. We present and discuss a model of IP traffic based on MMPP (Markov Modulated Poisson Process), which approximates LRD traffic by mimicking the hierarchical generation of data by Internet users. The MMPP model is capable of effectively capturing the key aspects of the traffic measured on an OBS edge router, hence representing an aggregation of the traffic generated by a number of sources.

The main contribution of this thesis is to derive an optimal Bayesian predictor for the burst size at the ingress router of an OBS network for MMPP approximations of LRD traffic. Bayesian prediction yields the MMSE (Minimum Mean Square Error) estimate of the burst size. As shown in a simulated OBS testbed, such Bayesian predictor can yield substantial improvement in latency reduction and service differentiation of OBS network compared to linear predictors, without substantial increasing in computational complexity.
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Chapter 1

Introduction

1.1 Background and Motivation of the Thesis

The development of the Internet has been made possible through the huge increase in bandwidth of worldwide optical networks. While capacity of transmission is growing rapidly, service providers now require a new generation of optical networking solutions to remain cost effective. Optical Burst Switching (OBS) is a promising hybrid approach between coarse grain optical circuit switching (OCS) and fine grain optical packet switching (OPS), see Figure 1.1. It allows switching of data channels entirely in the optical domain by doing resource allocation in the electronic domain. Therefore, it is considered a viable solution for terabit IP backbone. With the emergence of multitype applications such as data, voice, and videoconferencing, the next-generation network must also be designed to provide a variety of quality-of-service (QoS) functionalities.

The basic ideas underlying an OBS system are twofold: the burstification of IP packets, and the decoupling of the transmission and switching of a control header and its data payload. In an OBS network, various types of client data are aggregated at the ingress (an edge node) and transmitted as variable-size data bursts that are later disassembled at the egress node. Each data burst is preceded by a control header, also called burst header packet (BHP) [1], which is transmitted \( \Delta \) time units earlier in a separate control channel, and undergoes optical-electrical-optical (OEO) conversions, to set up a switching
path and reserve bandwidth at the core network. The time interval $\Delta$ that depicts how many time units the BHP precedes the data burst is called offset time. The essence of an OBS system is the decoupling of the BHP and its data payload, which enables data bursts to be transmitted transparently (without OEO) throughout the core network.

At present, OBS is attracting a lot of attention as a potential method by which future optical networks may use the available optical resources more effectively, i.e., achieving higher utilization. One of the main advantages of an OBS approach lies in its switching granularity, i.e., a data burst, shown in Figure 1.1. An OBS network can switch variable-size data bursts instead of individual IP packets. It is a solution to compensate for the time constraint of directly switching individual IP packets at optical routers due to the mismatch between the transmission capability of WDM fibers and the processing capability of the electronic control plane, thus alleviating the heavy burden of electronic devices for lightpath configuration. This advantage results from the particular procedure of burstification, whereby multiple IP packets are aggregated into a single data burst at the network ingress. A side effect imposed by such a burst-buildup process, however, is an
artificial delay. The typical end-to-end (ETE) delay of a data burst thus mainly consists of three components: burst assembly delay at edge routers, path setup delay caused by control headers, and the propagation delay in the core network.

In real-time bursts, it is imperative to discuss their ETE delay. The time for assembling a burst, which usually consists of hundreds of IP packets and is typically on the order of microsecond to millisecond, is designed to be comparable with the switching path setup time. The propagation delay, usually in the range of millisecond, is significant compared to the burst length. Therefore, one-way signalling protocol is widely investigated in today's research to avoid the two-way propagation delay. Meanwhile, we notice that the burst assembly delay can be further saved if we could transmit the BHP before the burst is completely assembled. The assembly delay at network edges is substantial and has a significant impact on the ETE burst delay. This influence is especially detrimental to the real-time traffic, which has stringent delay constraints. Since the propagation time of a data burst cannot be reduced, reducing burst delay at network ingresses will be greatly beneficial to latency reduction and QoS provisioning.

Like an OPS network, an OBS network can dynamically control system resources, assigning wavelengths of optical fiber to individual data bursts only when that user needs to transmit data. As one-way reservation scheme is adopted to avoid the two-way propagation delay, the data burst is sent out after a certain offset time, and does not wait to receive an acknowledgement from its BHP. Therefore, if the BHP reserved an insufficient bandwidth, its following data burst will be dropped at the core network, which will result in high burst loss and lead to burst retransmission. Since the BHP is transmitted before the burst assembly finished, the actual burst length is not known ahead of time and the burst length prediction is required. The incoming IP traffic characteristics have great influence on the prediction of burst length.
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Internet traffic presents long-range dependence (LRD), non-stationarity and multifractal scaling in short timescales. The ability to predict traffic patterns within an OBS network is one of the fundamental requirements of network design and management to facilitate QoS provisioning. A traditional linear predictor works well with short-range dependent (SRD) traffic, such as Poisson traffic, which is approaching uniform distribution after aggregation number over 1000. Therefore, linear predictors lose accuracy when feeding in LRD traffic, such as Fractional Brownian Motion (fBm). There exists direct fractional predictor [2] that could achieve a near-optimal prediction for fBm, but it is too complicated to implement. Recent studies have found that Markovian models, such as MMPP (Markov Modulated Poisson Process) and MAP (Markovian Arrival Process) are solvable mathematical traffic models that can approximate multifractal behaviour in finite time-scales [3].

There is significant motivation to construct an appropriate traffic model that leads to effective prediction algorithms for OBS networks, which yields a more precise prediction of burst length for the dynamic resource reservation. The choice of a prediction method is a tradeoff between the prediction interval, prediction error and computational cost. In this thesis, we present a traffic model based Bayesian (optimal) filter/predictor for OBS burst length prediction under MMPP traffic. We also compare the performance of the recursive Bayesian predictor with linear adaptive predictors, such as (least mean square) LMS-based filter in the following widely used criteria: (1), how far into the future can be predicted with confidence; (2), how much network resource has to be reserved to absorb the prediction uncertainty.

The objectives of this thesis can be summarized as follows:
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- Study the Internet traffic characteristics at OBS edge nodes, i.e., the input traffic at OBS ingress routers. Meanwhile, with the influence of long-range dependence of Internet traffic properties, we analyze the assembled traffic statistics as the output traffic at OBS ingress router.

- Examine the use of superimposed MMPPs (Markov Modulated Poisson Process) as an approximation to LRD Internet traffic, which mimics the hierarchical generation of data by Internet users. It is shown in [4] that the superposition of MMPPs has sufficient long-memory characteristics and is therefore more appropriate for modeling the aggregated sources in optical edge networks.

- Summarize and compare least mean square (LMS) based linear predictor and minimum mean square error (MMSE) based predictor in traffic prediction. According to our proposed traffic model MMPP, we derive a new prediction algorithm to optimize the tradeoff between efficiency and cost.

- We further need to implement our traffic models and prediction algorithms and investigate the performance by means of a simulation program in the OPNET environment.

1.2 Contributions

In order to make effective advanced bandwidth reservations for data bursts, a key requirement is that the BHP needs to have an accurate estimate of the size of the data burst. For simplicity of expression, we use a discrete-time stochastic state space model below to illustrate our methodology. It is important to keep in mind that the OBS burst length prediction problem considered in this thesis is a continuous-time stochastic state
space model, however the definitions below apply (with minor modification). Given the partially observed stochastic dynamical system

\[ x_{k+1} = f_\theta(x_k) + w_k \]
\[ y_{k+1} = h_\theta(x_k) + v_k, \]

where \( k = 0, 1, 2, \ldots \) denotes discrete time, \( f_\theta, h_\theta \) are known functions, \( w_k, v_k \) are independent white processes with known densities, our aim is to estimate the state \( x_{k+1} \) given the observation history of \( Y_k = (y_1, y_2, \ldots, y_k) \). The Bayesian state estimation is such a model-based optimal filtering, which assume the traffic model \( f_\theta(.) \) is known, and then estimate the state \( x_{k+1} \) by

\[ \hat{x}_{k+1|k} = E\{x_{k+1}|Y_k\} \]

using both Eqs. (1.1) and (1.2). The Bayesian estimate \( \hat{x}_k \)

\[ \hat{x}_k = E\{x_k|Y_k\} \]

is the minimum-variance error estimate by minimizing

\[ E\{(x_k - g(Y_k))^2\}, \]

where \( g(Y_k) \) is the estimate \( \hat{x}_k \). On the other hand, adaptive filtering uses the static observation Eq. (1.2), by assuming \( x_k \) is vary slowly with unknown dynamics \( \theta \). Since the computation of the optimal filter involves matrix manipulation, as shown in Section 4.2, the computational cost is on the order of \( N^2 \), while the adaptive filter only requires vector multiplication at the cost of \( N \), where \( N \) is the dimensions of the state space. In this thesis, we consider recursive Bayesian (optimal) filtering/prediction of MMPPs, which are partially observed continuous-time dynamical systems. Similar results to that described
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Traffic Model Approximation → MLE Parameter Estimation → Bayestian State Estimation

Figure 1.2: Three steps to predict burst size in an OBS network above hold for the optimal MMPP Bayesian prediction/estimation.

As shown in Figure 1.2, the main idea of our work contains 3 steps: 1), construct an appropriate traffic model for incoming IP traffic in the OBS edge networks; 2), estimate the model parameters by using a maximum likelihood estimate (MLE), for example using the expectation-maximization (EM) algorithm; 3), use Bayesian signal processing (predictor) to get the best state estimate. In this thesis, we focus on the first step, i.e., traffic model approximation and the third step, i.e., state estimation. We skip the second step by assuming that the model parameter is known by appropriate parameter estimation. The main contributions of this thesis are as follows:

- It is well known that the aggregated Internet traffic at the OBS ingress is self-similar. Based on the investigation of burst assembly mechanisms used at the OBS ingress router, we present to use a superposition of four independent 2-state MMPPs for approximating such self-similar traffic with LRD properties over sufficient time scales. The superposition results in a new 16-state MMPP model. Such MMPP approximations to LRD traffic are widely used in the literature [4][5].

- Using the above MMPP approximation, we derive an optimal recursive Bayesian traffic prediction algorithm, which dynamically predicts the burst duration of the OBS system. In the OBS network with advanced reservation (AR) applied, more accurate reservation gives a greater chance of success, and hence reduces burst loss
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probability. There are some studies in the literature focusing on linear prediction (LP) methods for traffic prediction, such as [6][7]. The choice of a prediction method is a tradeoff between the prediction interval, prediction error and computational cost. Numerical results of our experimental comparison show that our MMPP Bayesian predictor can substantially improve accuracy compared to adaptive LP without increasing computational complexity too much, i.e., from $O(16)$ to $O(16^2)$.

- The main advantage is that by using recursive Bayesian predictor for the MMPP traffic, accurate estimates of the burst size can be obtained. That is, the performance of OBS network on-line traffic prediction can be optimized in terms of end-to-end (ETE) delay and burst loss probability, which are the two fundamental issues of providing QoS differentiation when applying OBS to the next generation.

1.3 Thesis Overview

The rest of this thesis is organized as follows: Chapter 2 presents related work, including an overview of new techniques in today’s optical burst switching networks. Then we introduce the MMPP traffic modelling for self-similar traffic and generating method in Chapter 3. In Chapter 4, we give a detailed theoretic analysis of our proposed Bayesian MMPP predictor, with a comparison to LMS based linear predictor. In Chapter 5 we describe the OBS simulation testbed, present the simulation results for the proposed MMPP Bayesian prediction schemes and compare the analytical results. We further show that the simulation results also validate that our proposed MMPP predictor performs better than linear prediction. Finally, Chapter 6 concludes the thesis with a summary of the presented work and suggests future work.
Chapter 2

Literature Review and Related Work

In this chapter, we first give an introduction to optical burst switched (OBS) networks. A comparison between this new switching paradigm with other existing optical switching paradigms has been made, and it has been shown that OBS is not only cost-effective but also a viable solution for the next generation optical Internet. We provide a brief historical review of the early work on burst switching as well as the state of the art, including the prevailing protocol for OBS networks, called Just-Enough-Time (JET), and describe its major features and benefits.

Optical Networks, with their high transmission speed, are the ideal communication infrastructure to meet the ever increasing demand on bandwidth. With recent advances in wavelength division multiplexing (WDM) technology, the potential of fiber was fully realized. It is a technology to increase transmission capacity by transmitting data simultaneously at multiple carrier wavelengths. Bell Labs scientists have determined that with wavelengths and values typically used in optical networks today, it is theoretically possible to transmit data at 100 terabits per second without any excessive signal noise or interference [8]. Current commercial optical systems allow for the multiplexing of more than 160 wavelengths at 10Gbps each to get a total throughput of 1.6 terabits per second per fiber.
2.1 Optical Burst Switched Networks

2.1.1 Overview

Current WDM networks operate over point-to-point links, where optical-to-electrical-to-optical (OEO) conversion is required at each step. However, all future research is focused on all-optical networks (AONs) where user data travels entirely in the optical domain. The elimination of OEO conversion in AONs allows for unprecedented transmission rates. AONs can further be categorized as wavelength-routed optical networks (WRONs), optical burst switched networks (OBSNs), or optical packet switched networks (OPSNs).

Switching techniques primarily differ based on whether data will use switch cut-through or store and forward. The AON evolution (Figure 2.1) begins with the WRONs, which is also referred to as an optical circuit switched (OCS) network. In circuit switching, it is necessary to establish a dedicated path between the two stations. A call is first set up, the data is transferred and the call is disconnected. Resource reservation is done for the duration of the call. In optical circuit switched architecture, an end-to-end all-optical...
circuit, called lightpath, is established before the transmission of data signals, similar to a telephone line in public switched telephone networks. Circuit switching is advantageous when we have a constant data rate (fixed delays) on the network like voice traffic; however, it is not suitable under bursty traffic conditions, or when circuits are idle. The main constraint of WRONs is the limited number of wavelength per fiber. All-optical circuits tend to be inefficient for traffic that has not been groomed or statistically multiplexed, and are wasteful when the sustained traffic volume does not consume a full wavelength.

In packet switching, the data is broken into small packets and transmitted. The resources can be shared by the different sources. Optical packet switching (OPS) is a technology to transmit user data by means of optical packets, in which a wavelength is only allocated to a packet when it is transmitted, and it can be reused by others after the transmission. Packet switching works well with variable rate traffic like data traffic, and can achieve higher utilization. Therefore, OPS is more efficient and it can be used to support IP traffic and ATM traffic. However, OPS requires practical, cost-effective, and scalable implementations of optical buffering and optical header processing, which are server years away. Xu [9] reviews the OPS technology.

Circuit switching uses two-way reservation schemes that have a large round-trip time requirement. Packet switching, on the other hand, has a large buffer requirement and complicated control and strict synchronization issues. Optical burst switching (OBS) is a technology positioned between wavelength routing (i.e., circuit switching) and optical packet switching. OBS has the advantages of both circuit switching and packet switching, and is considered a promising protocol for all-optical networking. The benefit of OBS over circuit switching is that there is no need to dedicate a wavelength for each end-to-end connection. In addition, optical burst switching is more viable than optical packet switching as the burst data does not need to be buffered or processed at the cross connect.
Chapter 2. Literature Review and Related Work

This allows the strengths of optical switching technologies to be leveraged effectively and the problem of buffering in the optical domain to be circumvented.

Optical burst switching is based on the separation of the control plane and the data plane. Thus, costly OEO conversions are required only on a few control channels instead of a large number of data channels. In OBS networks, data packets are aggregated into much larger bursts before transmission through the network. This allows amortization of the switching overhead across multiple packets. There are two kinds of nodes in the OBS network: edge node and core node. The OBS edge nodes consist of an electronic router and a burst assembler while the OBS core nodes require an optical switching matrix, a switch control unit, and routing and signaling processors.

The main function of the OBS edge nodes is to collect traffic from various upper-layer users such as ATM switches, IP routers, etc. This collected data is sorted based on a destination address and is assembled into large variable-size units, called bursts, which are typically several hundreds of kilobytes in size. In addition, the OBS edge nodes create a control packet for each data burst, which contains burst length, offset time, and
all routing information, and is sent toward the destination at an offset time before the
burst itself (Figure 2.2 (a)). These control packets are electronically processed at each
intermediate node along the path, from the source to the destination. Their goal is to
set up the OBS core switches along the way, so that their corresponding bursts can travel
transparently in the optical domain through an bufferless or buffer limited network. The
data burst will later be disassembled at the OBS egress edge node (Figure 2.2 (b)). During
the assembly/disassembly, the client data is buffered at the edge, where electronic RAM is
cheap and abundant. There literature indicates that there are two ways to transmit these
signaling packets. One is to set up a completely separate electronic control network, such
as IP or ATM network, whereas mainly adopted way is to designate a specific wavelength
in an all-optical network, which can be considered as an out-of-band control channel. In
either case, the separation of control and data, both in time and physical space, is one of
the main advantages of OBS. It facilitates efficient electronic control while allowing for
great flexibility in the user data format and rate [10] because the bursts are transmitted
entirely over an optical signal and remain transparent throughout the network.

In general, all OBS designs include an offset time between the transmission of a control
packet and its corresponding burst. This offset allows the control packet to reserve the
needed resources along the path toward the destination before the burst arrival. Further­
more, the OBS core nodes need this offset time to pre-set their switching fabrics so that
the user data can “cut-through” without any buffers (Figure 2.3). There are variations in
the OBS literature, explained in the following sections, on how exactly to determine the
pre-transmission offset time and when to reserve the needed resources at the core nodes.
Despite their differences, however, all of the proposed OBS networks have a dynamic
operation, which has the potential for high resource utilization and adaptability.

Reference [11] describes a burst switch architecture design and operation, as well as
Chapter 2. Literature Review and Related Work

Figure 2.3: Functions at the optical cross-connect supporting OBS and MPLS

the concept of control channel, data burst, and head cell, etc. References [12][1] propose a network architecture such that the OBS network is the backbone of the Internet (IP network), and describe the architecture of an optical switch (router) with the functions that include burst control packet detecting, processing, and rewriting; forwarding table lookup; management of shared buffer (fiber delay line, or FDL); wavelength conversion; and data channel scheduling. Reference [13] studied access schemes in OBS for a metro ring architecture. As OBS becomes more mature, reference [14] discussed technical issues and general requirements for a transport layer architecture (i.e., services and protocols) for OBS networks.

2.1.2 OBS traffic shaping

One of the main functions of an OBS network is to collect upper-layer traffic, classify it and aggregate it into variable-size bursts. The classification and the proper assembly algorithm of small IP packets to larger optical bursts at edge nodes are essential for the performance of burst reservation, transmission and electronic control in core nodes, because it allows the network designers to control the characteristics and therefore shape the burst arrival traffic [15].
At the OBS edge node, incoming IP packets are classified based on the egress node and QoS class and stored in assembly queues accordingly. For burst assembly, two assembly algorithms are used as basic building blocks [16]: threshold-based and time-based schemes. In the first scheme, a burst is sent out when enough IP packets have been collected in the assembly queue such that the length of the resulting burst exceeds a threshold of $L_{\text{max}}$ bytes. In the second scheme, a time-out interval $T_{\text{max}}$ is set upon the arrival of the first IP packet to an empty queue. A burst consisting of all packets in the assembly queue is sent out as soon as a time-out occurs. The timer-based mechanism also includes the periodic and the non-periodic alternatives, whose intrinsic features are illustrated in Figure 2.4. In the periodic mechanism, the burst is assembled back-to-back. That is, the new burstification process begins as soon as the previous data burst is assembled and lasts until the pre-determined interval of $T_{\text{max}}$ elapses. A new data burst, however, is not actually generated if no packet arrives during the whole burstification interval. In the non-periodic assembly mechanism, the next burstification process starts only when a new IP packet arrives. Another variation of the time-based scheme ensures a minimum burst length $L_{\text{min}}$ by introducing padding bytes if necessary.

The characteristics of the output burst traffic can differ between the above algorithms. In the case of the pure threshold-based algorithm, burst traffic has the same self-similarity
as the input packet traffic. In the case of the time-based algorithm, burst traffic may have a smaller degree of self-similarity than packet traffic and therefore reduce the contention in the core network and make burst traffic smoother at short time scales. [17] studies the traffic characteristics while combining both criteria together, and concludes that the burst departures are not exponentially distributed but are correlated with the burst size.

2.1.3 OBS burst reservation protocols

There are three main components to set up a connection in OBS framework. The first one is the signaling procedure, which consists of creating the OBS control packets (BHP) and sending it an offset time ahead of its corresponding data burst. The other two are routing and wavelength allocation.

The various OBS signaling protocols that have appeared in the literature can be broadly classified by three dimensions: (1) the manner in which control is exercised in the network (i.e., distributed or centralized), (2) the reservation scheme used to hold wavelength resources for bursts, and (3) the method in which the offset value is calculated (and the purpose it serves).

By contrast with centralized signalling with end-to-end reservation in packet switching network, most of the proposed OBS architectures use a distributed one-way signaling procedure to set up a burst transmission path through the network. That is, the data burst is transmitted after a delay (known as the offset) of its control header (BHP), without waiting for a positive acknowledgment (ACK) that the entire path has been successfully established. Since OBS will most likely be implemented in long-haul networks, the main benefit of one-way reservation is that it halves the propagation delay, and therefore it will significantly decrease the time needed to establish a connection.
The manner in which output wavelengths are reserved for bursts is one of the principal differentiating factors among OBS variants. We distinguish between two types of reservations schemes: immediate and delayed.

Immediate reservation, exemplified by the Just-In-Time (JIT) family of OBS protocols [18], works as follows: an output wavelength is reserved for a burst immediately after the arrival of the corresponding setup message; if a wavelength cannot be reserved at that time, then the setup message is rejected and the corresponding burst is dropped.

The Horizon [11] and Just-Enough-Time (JET) [19] protocols employ a delayed reservation scheme, which operates as follows: an output wavelength is reserved for a burst just before the arrival of the first bit of the burst; if, upon the arrival of the setup message, it is determined that no wavelength can be reserved at the appropriate time, then the setup message is rejected and the corresponding burst is dropped. Most OBS time offsetting techniques are based on the assumption that the control packet is sent after the entire burst is assembled. A variation on these techniques is to send the control packet before collecting the entire burst from the upper layers, such as FRR (Forward Resource Reservation)[7]. The FRR scheme involves 3 steps: predict the data burst length before or during the burst assembly; pre-transmit the BHP for resource reservation before the data burst assembly is completed; when the burst assembly is completed, check whether the pre-reserved resource is sufficient to support the actual burst. The main advantage of this variation is the reduction in the burst pre-transmission delay. However, since the exact length of the burst is not included in the corresponding control packet, imperfect prediction regarding burst length may lead to overhead due to waisted bandwidth.

In the literature, the immediate reservation is also referred to as "explicit setup" and the delayed reservation is called "estimated setup." Similarly, an "explicit release" is used when the source sends an explicit trailing control packet to signify the end of a
burst transmission and to release the resources at all the intermediate nodes. Another possibility for wavelength release, termed as “estimated release,” requires that the initial control packet contain the oncoming burst length and thus the OBS core node would know exactly the end of the burst transmission and would automatically release the occupied resources.

Based on this classification, the four possibilities in an OBS network are: explicit setup/explicit release, explicit setup/estimated release, estimated setup/explicit release and estimated setup/estimated release. Overall, there no clear winner between these schemes, and each has advantages and disadvantages. For example, the estimated schemes occupy resources for shorter times, and therefore they can achieve a higher network throughput. The difficulty with these schemes, however, lies in the fact that they are inherently quite complicated and their performance greatly depends on whether the estimates are correct. By contrast, the explicit setup/explicit release scheme is much easier to implement but it occupies resources for longer periods than the actual burst transmission, and therefore it may result in higher burst loss probability.

2.1.4 Contention resolution

In OBS, when one-way reservation schemes (e.g., JIT, JET, and Horizon) are adopted, it is possible that two bursts compete for the same output port; thus contention may arise. Such a contention situation can be resolved through one or a combination of the following three domains:

- Wavelength domain: By means of a wavelength converter, a burst can be sent on a different wavelength channel to the designated output fiber. Thus, all the wavelength channels of an output fiber can be considered a single shared bundle of
channels.

- Time domain: In a fiber delay line (FDL) buffer, a burst can be delayed until the contention situation is resolved and the wavelength becomes available. In contrast to buffers in the electronic domain, FDLs provide only a fixed delay, and data bursts leave an FDL in the same order in which they entered. That is, they do not have random access functionality.

- Space domain: In deflection routing, a burst is sent to a different output fiber of the node and consequently on a different route towards its destination node. Thus, deflection uses the entire network as a shared resource for contention resolution.

Almost all work on OBS assumes contention resolution by full wavelength conversion. That is, a dedicated wavelength converter is provided for each input or output wavelength. For a low to medium load, this provides a low burst loss probability because all wavelength channels of an output fiber can be shared among all bursts directed towards this output fiber. For a high load, the number of wavelength channels has to be very large to reach burst loss probabilities of $10^{-6}$ or less, e.g., 350 wavelength channels are needed to carry a load of 0.8 Erlang per wavelength channel at this loss rate.

Wavelength conversion has also been complemented by providing a number of FDLs in an FDL buffer. It can be seen that the application of an FDL buffer has a significantly reduced burst loss probability compared to the bufferless case. When using FDL buffers in OBS nodes, the physical length of the FDL has to be considered. Even if the FDLs are dispersion compensated if needed, the maximum length of an FDL is limited by the power budget. Thus, combining performance and technology arguments, mean burst lengths in the order of Mbytes cannot be realistically stored in FDL buffers.
Deflection routing has also been analyzed in the context of OBS for irregular mesh networks [20][21]. In general, the path a deflected burst takes through the network should be as short as possible to minimize resource consumption. In OBS schemes which apply offset times, the problem of insufficient offset times has to be avoided. That is, it has to be ensured that there always be a large enough offset between control packet and data burst even if extra nodes are traversed. Thus, [20] proposes to use FDL buffers to increase offset times in intermediate nodes prior to deflection.

By an intelligent combination of different contention resolution strategies, the cost and performance of OBS nodes can be optimized. Burst segmentation or composite burst switching is an approach for contention resolution that is based solely on burst scheduling: It tries to minimize the data volume discarded by not dropping an entire burst but dropping only that part of a burst that actually conflicts with another burst [22][23].

## 2.2 Related Work on Traffic Models in OBS Network

Traffic models play very important roles in the planning, design and analysis of communication networks. Different models have different results, and the discrepancy between the results using different models can be huge. Applications of traffic models include resource allocation, call admission control and QoS provisioning.

In the design of OBS networks, a major aim is to solve the problem of the mismatch between extremely high optical transmission rates and the relatively slower electronic processing. Burst assembly is required at the OBS edge nodes, where short IP packets
are demultiplexed according to their destination and gathered into larger size packets. These super packets are also called bursts. The outcoming burst traffic from the edge node will depend highly on the incoming IP traffic and the burst assembly algorithm.

Internet IP traffic has been demonstrated to affect network performance by two kinds of bursty property: short-range dependent (SRD) burstiness and long-range dependent (LRD) burstiness. Memoryless Poisson models were assumed in the OBS network in the past few years; however, recently, there has been a significant change in the understanding of network traffic. Poisson models for network traffic become essentially uniform when aggregated by a factor of 1,000; while actual network traffic shows no such decrease in variability over the same range of aggregation. Numerous studies have found that data traffic in high-speed networks exhibits self-similarity that cannot be captured by classical models. Traditional Markov models and Regression models can only capture short range dependencies in traffic. In a classical Markov chain, the next state of the system depends only on the current state. Regression models define explicitly the next random variable in the sequence by previous ones within a specified time window and a moving average of white noise.

The degree of self-similarity, defined by the Hurst parameter, typically depends on the utilization level of the network and can be used to measure the "burstiness" of the traffic. The Hurst parameter is basically a measure of the speed of decay of the tail of the autocorrelation function; as H increases the degree of self similarity increases. If \(0.5 < H < 1\), then the process is long-range dependence (LRD), and if \(0 < H < 0.5\), then it is short-range dependence (SRD). Hence, \(H\) is widely used to capture the intensity of the long-range dependence of a traffic process. The closer \(H\) is to 1 the more long-range dependent the traffic is, and vice versa.

In this section we review some long-memory models, which are widely used in theory
and practice to model self-similar traffic. The observation of LRD property in the Internet traffic has initiated studies of new models such as chaotic maps [24], fractional Brownian motion (fBm) models [25], fractional Gaussian noise (fGn), and fractional autoregressive integrated moving average (FARIMA) [26]. fBm is a non-stationary stochastic process developed as a generalization of the standard Brownian motion model. fGn is a stationary process. fGn is related to fBm, since fGn is produced by taking the differences in fBm realizations. They can describe self-similar behavior in a relatively simple manner. Wavelet analysis was shown to be one of the most powerful methods for the description of stochastic properties of traffic, which takes explicitly into account a multi-fractal model as in [27]. The main advantage of these models, especially when multifractality is taken into account, is their rich scale-invariance property. These models are computationally efficient, but they suffer for the lack of a simple mapping between the traffic parameters and the model coefficients. The queuing theoretical techniques developed in the past are hardly applicable to these models.

On the other hand, a number of models based on traditional traffic models have been proposed. One approach is to emulate self-similarity over a certain range of time scales with finite state Markovian models. [28][4] have proposed a model based on the Markov Modulated Poisson Process (MMPP) as a superposition of two-state Markov processes. MMPP is considered as the best Markov process to emulate LRD and scale invariance [3]. In this work we will also apply such an approach.

2.3 Related Work on Traffic Prediction

In an OBS network, the burst reservation message provides a report of the incoming burst length in a tell-and-go fashion along the path from source (ingress edge node) to
destination (egress edge node). Note that there is a packetization delay, due to the burst assembly time, which is inherent to burst switching. When to send the reservation message to the core network belongs in the scope of QoS provisioning. Burst length prediction is required if the reservation signaling message is sent before burst assembly finishes. Linear predictor is the simplest one, which does not need prior knowledge of incoming traffic patterns, and suitable for any traffic model. In the literature, some studies propose to use the least mean square (LMS) based linear prediction method to predict the burst length in the OBS network [6][7]. Another more sophisticated non-linear method is MMSE (minimum mean square error) predictor, which aims to minimize the expected value of the squared prediction error, and also works for on-line prediction that does not require the underlying structure of the incoming traffic. On the other hand, the quality of the prediction depends on the amount of uncertainty, which in turn depends on a number of factors, including the amount of traffic history used to make the prediction, the prediction horizon, and the nature of traffic itself. Predictors based on traffic structure have the significant benefit of computing the weight factor on history samples. Considering the abundant evidence that high-speed network traffic is self-similar and long-range dependent (LRD) in nature and the fact that the history of LRD processes has a significant impact on the present value of the process, it is natural to assume that predicting LRD traffic would be rather rewarding. There are particular predictors [2] based on fractional traffic models, such as fBm and fGn processes. From the engineering perspective, these fractional predictors are too complicated to implement and time-consuming when doing dynamic bandwidth reservations.
Chapter 3

Self-Similar Traffic and MMPP Approximation

It is well known that the characteristics of aggregated Internet traffic at the OBS ingress nodes is fractal and can be described in terms of self-similar stochastic processes. However, in the last few years, considerable effort has been devoted to studying the OBS burst traffic after assembly, as the burst size distribution determines the optical buffering requirements. Therefore, the self-similarity of OBS burst traffic has a significant impact on the overall network performance, e.g., burst blocking probability. Self-similarity indicates long-range dependence (LRD) in the correlation structure of network traffic. Generally speaking, although the incoming packet traffic is aggregated in OBS assembly nodes, the number of assembled burst input flows in the OBS core node is in fact not large, and not enough to be aggregated to Poisson burst traffic. Furthermore, the claim that burst assembly could reduce traffic self-similarity [29] was disproved by analysis and the simulation of both synthetic traffic and traffic traces [30][31].

In this chapter, we show first special interest on how the self-similarity features of incoming traffic affect the burst size distribution. Then we propose to use MMPP approximation to represent the aggregated Internet traffic at the OBS edge. The traffic generation of this special MMPP model is also provided.
3.1 LRD Properties and Self-Similar Traffic

As the term implies, long-range dependence refers to a correlation structure that decays at a rate much slower than the exponential decrease that occurs in the correlations of a short-range dependent (SRD) process. An interesting characteristic of the correlation structure of a long-range dependent process is that its autocorrelation obeys the well-known power-law distribution. That is, for a stationary LRD process \( \{X_t\}, t = 0, 1, 2, \ldots \) with mean \( \mu \), variance \( \sigma^2 \) and autocorrelation function \( r_{LRD}(k) \), we have

\[
    r_{LRD}(k) \sim k^{-\beta}, \text{ as } k \to \infty, \text{ where } (0 < \beta < 1)
\]  

Thus the autocorrelation function of such a process decays hyperbolically. Hyperbolical decay is much slower than exponential decay, and since \( \beta < 1 \), the sum of the autocorrelation values of such a series approaches infinity. This description is closely associated to self-similarity and a \textit{Hurst parameter} defined by the equation:

\[
    H = 1 - \beta/2
\]  

As we stated in section 2.2, the \textit{Hurst parameter} \( H \) is the index of self-similarity. That is, for general self-similar processes, it measures the degree of "self-similarity." When the parameter lies in the interval \((0.5, 1)\), the resulting self-similar process exhibits long-range dependence as defined in Eq.(3.2).

In contrast, a short-range dependent process requires that its autocorrelation function of \( \{X_t\} \) decays exponentially to zero. That is, \( \{X_t\} \) would have a correlation function \( r_{SRD}(k) \) decreased according to

\[
    r_{SRD}(k) \to C^k, \text{ as } k \to \infty, \text{ where } -1 < C < 1.
\]
Chapter 3. Self-Similar Traffic and MMPP Approximation

Common traffic models with LRD are based on self-similar processes. Intuitively, a process is self-similar if its statistical behavior is independent of the time-scale. In other words, the characteristics of a self-similar process look the same at any time scale. This feature means that averaging over equal periods of time does not change the statistical characteristics of the process.

Consider the above stationary time series \( \{X_t\}, t = 0, 1, 2, ..., \) with zero mean and autocorrelation function \( r(k) \), representing the number of packets during time intervals observed on a given link, where \( r(k) \) is given as

\[
\text{Consider the above stationary time series } \{X_t\}, t = 0, 1, 2, ..., \text{ with zero mean and autocorrelation function } r(k), \text{ representing the number of packets during time intervals observed on a given link, where } r(k) \text{ is given as }
\]

\[
X_t = \frac{1}{m} \sum_{i=1}^{m} X_{(t-1)m+i}, \quad t = 1, 2, ...
\]

(3.5)

The processes \( \{X_t^{(m)}\} \) are also wide sense stationary with mean \( \mu \) and autocorrelation \( r^{(m)}(k) \). There are different classes of self-similarity:

- **Exact Self-Similar**: the process \( \{X_t\} \) is said to be exactly self-similar if for all \( m = 1, 2, ..., \) it satisfies

\[
r^{(m)}(k) = r(k).
\]

(3.6)

(3.6) also implies an equivalent definition:

\[
Var(X^{(m)}) = m^{-\beta}Var(X), \text{ for all } m, \text{ and } 0 < \beta < 1.
\]

(3.7)
In other words, the autocorrelation structure is preserved across different time scales.

- Asymptotic Self-Similar: the process \( \{X_t\} \) is said to be asymptotically self-similar if for all \( k \) large enough,

\[
r^{(m)}(k) \to r(k), \text{ when } m \to \infty.
\]  

which could also be represented by:

\[
\text{Var}(X^{(m)}) \sim m^{-\beta} \text{Var}(X), \text{ as } m \to \infty, \text{ where } 0 < \beta < 1.
\]  

- Stochastic Self-Similar: This is a continuous time definition. The process \( \{X_t\} \) is statistically self-similar with the parameter \( H \), if for any positive stretching factor \( a \), the re-scaled process with time scale \( at \), \( a^{-H}X_{at} \) is equal in distribution to the original process \( \{X_t\} \), and they satisfy the relation

\[
X_{at} \approx a^{-H}X_t, \text{ for all } (a > 0),
\]  

where \( \approx \) denotes equality in distribution. This is a very strict form of self-similarity called self-similarity with stationary increments. FBm is an example of such a process.

Taking the logarithm of both sides of Eq. (3.7) gives the following equation:

\[
\log_{10} \left( \text{Var}(X^{(m)}) \right) = \log_{10} \text{Var}(X) - \beta \log_{10} (m)
\]  

The variance-time plot (Fig.3.1), often used to test traffic for self-similar properties, is based on this equation. Self-similar traffic results in a straight line with slope \( \beta \in [-1, 0] \).
For successive values of $m$ that are equidistant on a log scale, the logarithm of sample variance of $X^{(m)}$ is plotted versus $m$ on a log-log plot. Therefore, in practice, the most common way to validate if a generated process is LRD is by fitting a least-square line to the points of the plot and then calculating its slope. An estimate of the Hurst parameter is obtained as $\hat{H} = 1 - \frac{slope}{2}$.

The relation between self-similarity and LRD is that if a process $\{X_t\}$ is self-similar with Hurst parameter $H$, then its increment process $Y_t = X_{t+s} - X_s$ is LRD with parameter $H$. 

Figure 3.1: Variance-time plot
3.2 Influence of self-similar traffic in OBS

3.2.1 Influence on burst size distribution

The distribution of burst length can be influenced by offered traffic and burst assembly parameters. In general, according to Central Limit Theorem (CLT), by aggregating IP packets into bursts, the burst size distribution will approach Gaussian distribution as the number of packet arrivals goes up or the assembled burst size goes up, as verified by our simulation results. On the other hand, the influence of self-similarity (H parameter) is significant, especially as the timeout value grows. This is due to the fact that, as the H parameter grows, the variance of the traffic sample mean (aggregated traffic) decays more slowly than in the independent case (H=0.5). Thus, the larger the H parameter the larger the burst size variance. As discussed in Chapter 2.1.2, the traffic shaping (burst assembly) at the OBS edge node can smooth traffic on short time-scales, i.e., reducing its variability. If the correlation extends only over timescales smaller than a burst assembly period, the correlation in the packet traffic process is shaped away by burstification; i.e., it will not be observed in the burst traffic process. If, on the other hand, the correlation extends over timescales much larger than a burst assembly period, burstification will not shape it away, so that a similar correlation structure will exist in both packet and burst traffic streams. Longer assembly times lead to improved smoothing.

3.2.2 Methodology

Motivated by the above observation, we now introduce a simple Markovian approach to approximate the self-similar traffic over sufficient time scales for burstification at OBS edge nodes. In traffic modelling, a superposition of several MMPPs is practically sufficient
to represent self-similarity over several time-scales to model the real traffic. We construct an MMPP with apparently self-similar behaviour over several time-scales by superposing several MMPPs. First, consider two-state MMPPs with different time-scales. That is, the mean sojourn time of each process is in accordance with the different time-scale. Let us superimpose them to make a new MMPP. When we see this process on a large time-scale, it looks like an ordinary two-state MMPP. If we look on a smaller time-scale, we find that each state is composed of a smaller MMPP. If we look on a still smaller time-scale, we find that each state of a smaller MMPP is again composed of a still smaller MMPP. This can be repeated only a finite number of times. It is impossible to measure given traffic during an infinite amount of time. Thus, it is in practice sufficient to use the process that has self-similarity over only several time-scales to model the real traffic. Refer to [4][5] for details.

We use a continuous-time discrete-state MMPP for modeling the self-similar traffic. That is, for our OBS system with self-similar traffic input, we assume first that the traffic carried by each forward equivalence class (FEC) is a MMPP and that MMPPs are independent of one another. The OBS network supports several FECs from different edge OBS shapers, which are assumed to have the same mean, variance and Hurst parameter, without loss of generality.

3.3 MMPP Approximation and Generation

3.3.1 Definitions and properties of MMPP

In this section, we summarize some of the main characteristics of MMPP defined on a probability space. MMPP is a doubly stochastic Poisson process where the intensity of
Chapter 3. Self-Similar Traffic and MMPP Approximation

A Poisson process is defined by the state of a Markov chain. The Markov chain can therefore be said to modulate the Poisson process, hence the name. Now, let \( \{X_t\} \) be a continuous-time \( S \)-state Markov chain, without loss of generality, defined on the state space \( \mathbf{e} = \{e_1, e_2, ..., e_S\} \), where \( e_i \in \mathbb{R}^S \) is the unit vector with 1 in the \( i \)-th position. This Markov chain modulates an integrable Poisson traffic rate process; hence in this \( S \)-state MMPP, the packet arrival rate is determined by the state of the continuous-time Markov chain with infinitesimal generator \( Q \) and Poisson arrival rate \( \lambda_i, i \in \{1, S\} \). That is, the traffic rate process behaves as a Poisson process with arrival rate \( \lambda_i \) when the Markov chain is in state \( i \). Both the Markov chain and Poisson process can have simultaneous jumps. Transitions between states are dependent and governed by the above continuous-time Markov chain. \( Q \) is also known as the \textit{transition rate matrix} of the modulating Markov chain.

\[
Q = \begin{bmatrix}
\theta_{11} & \theta_{12} & \cdots & \theta_{1S} \\
\theta_{21} & \theta_{22} & \cdots & \theta_{2S} \\
\vdots & \vdots & \ddots & \vdots \\
\theta_{S1} & \theta_{S2} & \cdots & \theta_{SS}
\end{bmatrix}
\]

which equals

\[
\sum_{j=1}^{S} \theta_{ij} = 0, \forall i \in \{1, 2, ..., S\}.
\]

Define the \textit{arrival rate matrix} \( \Lambda = \text{diag}[\lambda_1, \lambda_2, ..., \lambda_S] \), whose diagonal elements contains the arrival intensities that corresponds to the different states of the Markov chain.

Also define \( P\{X_t = i\} = p_t^i, i \in \{1, 2, ..., S\} \). Then the transition probability distribution \( p_t = (p_t^1 p_t^2 ... p_t^S)' \) should be \([e^{Q't}]\), which satisfies the forward equation \( \frac{dp_t}{dt} = Q'p_t \), where \('\)' denotes the transpose operation.

Let \( N_t \) denote the above Markov chain \( \{X_t\} \) modulated Poisson process, which repre-
sents the number of events that occur during the interval \([0, t]\). For the time-stationary MMPP, the mean of \(N_t\) is given by [33]

\[
E\{N_t\} = \pi \Lambda t,
\]

where \(\pi = [\pi_1, \pi_2, ..., \pi_S]\) is the steady state vector of the Markov chain such that

\[
\pi Q = 0, \quad \pi e = 1
\]

### 3.3.2 MMPP traffic generation model

We use a continuous-time MMPP for modeling the self-similar traffic. We construct an MMPP with apparently self-similar behaviour over several time-scales by superimposing several MMPPs. First, consider two-state MMPPs with different time-scales. That is, the mean sojourn time of each process is in accordance with the different time-scales. Let us superimpose them to make a new MMPP. When we see this process in a large time-scale, it looks like an ordinary two-state MMPP. If we look at a smaller time-scale, we find that each state is composed of a smaller MMPP. If we look at a still smaller time-scale, we find that each state of a smaller MMPP is again composed of a still smaller MMPP. This can be repeated only a finite number of times. Therefore, the MMPP is not self-similar according to the definitions in the previous section because it looks constant when time-scale is larger than the time constant in itself. However, it can emulate self-similarity over several time-scales. It is impossible to measure given traffic during an infinite amount of time. It has also been observed that high-speed traffic loses self-similarity over days [34]. Thus, it is practically sufficient to use the process which has self-similarity over only several time-scales to model the real traffic. Now we assume that the number of the states
Table 3.1: Parameter setting for superposition of MMPPs

<table>
<thead>
<tr>
<th>source</th>
<th>$\lambda_i$</th>
<th>$\sigma_{1i}$</th>
<th>$\sigma_{2i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$IPP_1$</td>
<td>6.579</td>
<td>$5.715 \times 10^{-1}$</td>
<td>$2.285 \times 10^{-1}$</td>
</tr>
<tr>
<td>$IPP_2$</td>
<td>2.562</td>
<td>$1.231 \times 10^{-2}$</td>
<td>$4.923 \times 10^{-3}$</td>
</tr>
<tr>
<td>$IPP_3$</td>
<td>0.914</td>
<td>$2.653 \times 10^{-4}$</td>
<td>$1.061 \times 10^{-4}$</td>
</tr>
<tr>
<td>$IPP_4$</td>
<td>0.448</td>
<td>$5.715 \times 10^{-6}$</td>
<td>$2.285 \times 10^{-6}$</td>
</tr>
<tr>
<td>Pois.</td>
<td></td>
<td></td>
<td>$\lambda_p = 0$</td>
</tr>
</tbody>
</table>

Note that the four 2-state MMPP traffic sources are independent. At OBS edge node, the incoming IP traffic itself is self-similar aggregated traffic, and is demultiplexed at the
edge shaper according to each FEC in separate queues, based on the destination and QoS requirement. We assume each FEC traffic is also self-similar and can be represented as the superposition of the above four IPPs. The superposition can be described as follows:

\[
Q = Q_1 \oplus Q_2 \oplus Q_3 \oplus Q_4 \tag{3.17}
\]
\[
\Lambda = \Lambda_1 \oplus \Lambda_2 \oplus \Lambda_3 \oplus \Lambda_4 \oplus \lambda_p \tag{3.18}
\]

where \(\oplus\) denotes the Kronecker’s sum and \(\lambda_p\) is the arrival rate of the Poisson process to be superposed. The mean arrival rate \(\lambda\) of each FEC traffic process can be calculated as:

\[
\lambda = \lambda_p + \sum_{i=1}^{4} \frac{\lambda_i}{2} \tag{3.19}
\]

We denote the MMPP obtained by the superposition of IPPs as the stochastic process \(\{N_t, t \geq 0\}\). This MMPP \(N_t\) has an underlying 16-state continuous-time Markov chain which we denoted as \(\{X_t, t \geq 0\}\) in the previous section, with transition rate matrix \(Q\) (3.17) and arrival rate matrix \(\Lambda\) (3.18), representing aggregated FEC traffic sources as an input at the OBS edge node, with LRD properties. The Markov chain \(X_t\) generates the MMPP \(N_t\) as

\[
N_t = \int_0^t g' X_s ds + m_t, \tag{3.20}
\]

where the superscript ' denotes vector transpose, \(N_t\) denotes the IP packet arrivals that occur during the interval \([0,t]\), and \(g = [\lambda_1, \lambda_2, ..., \lambda_{16}]'\) is the vector of intensities of the process \(N_t\) and \(m_t\) is a Poisson martingale stochastic process, which satisfies

\[
\mathbb{E}\{m_\tau | N_t\} = m_t, \text{ for } \tau > t, \tag{3.21}
\]

where \(N_t\) is the observation history of the MMPP \(N_t\), and \(\mathbb{E}\{\cdot\}\) denotes the expectation operator.
Again, since the 16-state worked well for modeling self-similar behaviour over four to five time scales, we choose 16-state for our Markov chain. One example of the transition rate matrix Q generated from Table 3.1 in our simulation is shown below:

$$
\begin{bmatrix}
-0.58 & 0.00 & 0.00 & 0 & 0.01 & 0 & 0 & 0 & 0.57 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.00 & -0.58 & 0 & 0.00 & 0 & 0.01 & 0 & 0 & 0 & 0.57 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.00 & 0 & -0.58 & 0.00 & 0 & 0 & 0.01 & 0 & 0 & 0 & 0.57 & 0 & 0 & 0 & 0 & 0 & 0 \\
0.00 & 0 & 0 & -0.58 & 0.00 & 0 & 0 & 0.01 & 0 & 0 & 0 & 0.57 & 0 & 0 & 0 & 0 & 0 \\
0.00 & 0 & 0 & 0 & -0.58 & 0.00 & 0 & 0 & 0 & 0.01 & 0 & 0 & 0 & 0.57 & 0 & 0 & 0 \\
0.00 & 0 & 0 & 0 & 0 & -0.58 & 0.00 & 0 & 0 & 0 & 0.01 & 0 & 0 & 0 & 0.57 & 0 & 0 \\
0.00 & 0 & 0 & 0 & 0 & 0 & -0.58 & 0.00 & 0 & 0 & 0 & 0.01 & 0 & 0 & 0 & 0 & 0.57 \\
0.23 & 0 & 0 & 0 & 0 & 0 & 0 & -0.24 & 0.00 & 0.00 & 0.01 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}
$$
Chapter 4

Traffic prediction in OBS network

In this chapter we look at the problem of OBS traffic prediction in the presence of self-similarity. One of the key issues in QoS provisioning in the OBS network is to predict the optical burst length in the next burst assembly time interval based on the online measurements of traffic characteristics. The goal is to forecast future traffic variations as precisely as possible, based on the measured traffic history. Traffic prediction requires accurate traffic models that can capture the statistical characteristics of actual traffic. Inaccurate models may overestimate or underestimate network traffic. While a certain amount of error is allowable (and expected), the overall predictor is required to be accurate enough so as not to reduce utilization in the worst cases.

We start from investigating the BHP pre-transmission mechanisms in OBS networks for QoS provisioning, where the LMS-based linear predictor is assumed. We then derive an optimal prediction algorithm in the MMPP predictor sense and discuss further the implementation aspects of our proposed algorithm.
4.1 Pre-Reservation and Linear Predictor

As we have introduced that, different offset-time based approaches have been proposed to provide service differentiation in OBS networks. The common purpose is trying to manage QoS on a class-by-class basis using different extra offset times for different classes of bursts. The basic idea is that by giving a larger extra offset time to a higher priority class, reservation for higher priority bursts can be made far in advance of lower priority bursts and thus have a better chance to succeed. Although offset-time based differentiation is easy to implement and provides efficient isolation between service classes when a sufficiently large extra offset time is assigned to higher priority bursts, the extra offset time introduces an additional delay at the edge. A variation on these approaches is to send the control packet (BHP) prior to collecting the entire burst from the upper layers. The main advantage of this variation is the reduction in the burst pre-transmission delay. However, the control packet is sent before the burst is completely assembled; therefore the estimation of burst length is required in the OBS edge node in order to utilize the estimated setup/estimated release scheme.

For simplicity, we divide the incoming IP traffic into two classes, i.e., low-priority (delay tolerant) and high-priority (delay sensitive), and apply burst-size prediction for high-priority traffic. Only basic offset time, \( \tau_0 \) is considered. That is, the BHP is transmitted \( \tau_0 \) time units before the data burst so that the BHP can set up a switching path and reserve bandwidth. Both classes of traffic use the estimated setup/estimated release scheme. However, the low-priority traffic uses the Just Enough Time (JET) signaling protocol [19], where the occupation of the resources is exactly from the burst arrival until the transmission of its last bit. The BHP is sent after the entire burst is completely assembled and no estimation is made. The bursts still wait in the queue and will be transmitted to the OBS core after a certain offset time \( \tau_o \). We assume that the offset time is short.
Figure 4.1: Service differentiation at OBS ingress node with traffic prediction and constant (equals to burst assembly time in most cases). Thus the influence of the offset time in the data burst arrival process is only a time shift. This scheme is termed as delayed reservation. For high-priority traffic, we use FRR signaling protocol [7], a so-called advanced reservation scheme, where BHP is sent before the burst is completely assembled, and the estimation of burst length is made by a predictor between the traffic classifier and the burstification control unit (BCU). Figure 4.1 shows this scenario under analysis. A key requirement for successful implementation of FRR is that the BHP needs to have an accurate estimate of the size the data burst. We now briefly introduce how traffic prediction works for bandwidth reservation in OBS networks.

The OBS ingress node performs the grouping of a number of small IP packets in variable-size bursts before transmitting them to the optical domain. As MPLS traffic engineering is deployed, the IP packets given same destination address and QoS requirement are classified into one forward equivalent class (FEC) and are assigned with the same label. The OBS ingress node maintains a separate queue per FEC. The classified traffic of per FEC is assumed self-similar with long-range dependence (LRD) in property, which is approximated as an MMPP process in the previous chapter. In our system, we use a timer-based non-periodic burst assembly mechanism, described in section 2.1.2. Figure 4.2 depicts how the predictor works while burst assembling.
Assume the $k$th burst has been transmitted down the optical network, and let $\tau_{1}^{(k+1)}$ denotes the arrival time of the first new IP packet, which will be assigned to the $(k+1)$th data burst. Upon a timeout expiration, the burst is framed and relayed for transmission. As a result, the burst assembly time $\tau_{a}$ is kept within the timeout value, which is independent of network load. On the other hand, prior to burst transmission, a control header (BHP), with burst label, predicted burst size, etc., has to be released to reserve the necessary bandwidth at each intermediate node in the OBS core network. As shown in Figure 4.2, the BHP is sent at the time $\tau_{1}^{(k+1)} + \tau_{a} - \Delta$, where $0 \leq \Delta \leq \tau_{a}$. The number of packets arriving during the time interval $\Delta$ is not known at this time, so the BHP needs to predict the number of packets arriving from $\tau_{1}^{(k+1)} + \tau_{a} - \Delta$ to $\tau_{1}^{(k+1)} + \tau_{a}$ in order to specify the reservation duration. $\Delta$ is termed as prediction interval in traffic prediction, and in our case $\Delta$ is physically equal to offset time $\tau_{o}$. Varying $\Delta$ is a way of service differentiation for different QoS requirements. Since we only consider two classes of traffic in our system, we can simply choose $\Delta = \tau_{a}$. That is, we predict the $(k+1)$th burst size at the time its first packet arriving.

It is usually difficult to make a prediction algorithm practical, while accurate and effective, especially for the self-similar traffic. Among these widely used estimations derived from a mean square error based method, linear predictive filter (LPF) adopted in [7] is
Before deriving the Bayesian predictor we first briefly outline the linear prediction method for predicting burst size. With the knowledge of the burst length of the last $N$ bursts, $(L_{k-N}, ..., L_k)$, the length of the next incoming burst $L_{k+1}$ could be expressed as a linear combination of the lengths of the previous $N$ bursts by:

$$\hat{L}_{k+1} = \sum_{i=1}^{N} w(i) \cdot L_{k-i+1}$$

where $w(i), i \in \{1, ..., N\}$ are the coefficients of the linear predictor. These are typically updated by an adaptive filtering type algorithm such as the normalized LMS (Least Mean Square) algorithm [35]. Another benefit of using LMS is that there is no need to know the underlying structure of traffic.

A control header makes an advanced resource reservation according to the predicted value. If the prediction is optimal, the predicted value should be equal to the actual incoming burst length. Analyzing the performance of prediction techniques and the predictability of network is an important study in the OBS network. The quality of a prediction depends on the amount of uncertainty that accompanies the prediction, and mathematically this is measured by the variance of the prediction error. We modelled the LRD traffic as Markov Modulated Poisson Process (MMPP), which matches correlation lags over four to five orders of magnitude. The linear predictor compute only a moving average of the $N$ past burst lengths. A major deficiency is that it does not use knowledge about the MMPP structure to predict the burst length. We now introduce an optimal (conditional mean) Bayesian prediction algorithm for predicting the OBS burst size when the traffic is for LRD traffic approximated by an MMPP model. Bayesian estimation is optimal in the sense of minimum-variance.
4.2 MMPP Bayesian Predictor

In the previous chapter, we introduced a 16-state MMPP model as a superposition of four independent 2-state MMPPs for modelling OBS incoming traffic in finite time scales. We now derive a recursive Bayesian predictor based on this MMPP model, which calculates a new estimate for each time-step, based on the previous estimate and new measurements. Recursive Bayesian estimation works by simulating the process, while at the same time adjusting it to account for new measurements, taken from the real process.

For simplicity, we assume IP packet sizes are fixed in our system, i.e., equal, and the burst length is measured in the number of packets in the burst. As we introduced in section 3.3, in a state space model, for each FEC, let the classified IP traffic be represented as MMPP \( N_t \) process, i.e., \( N_t \) denotes the number of IP packet arrivals that occur during the interval \([0,t]\). And let \( J \) denote the MMPP observation history, i.e., the times of arrivals of all the packets up to time \( t \). (Note that the observation history can be defined more rigorously in measure theoretic notation in terms of sigma algebras.) Given the observation history \( J^{(k+1)} \), our aim is to predict the \((k+1)\)th burst size \( L_{k+1} \), i.e., the number of IP packet arrivals in the time interval \( [\tau^{(k+1)}, \tau^{(k+1)} + \tau_a] \). The best prediction of \( L_{k+1} \) can be derived by the Bayesian estimation algorithm, i.e., computing \( \mathbb{E}\{L_{k+1} | J^{(k+1)}\} \), which is the minimum mean square error (MMSE) estimate. In order to derive the Bayesian predictor for the burst length \( L_{k+1} \), it is first necessary to derive the optimal state estimate \( \hat{X}_t \) of the underlying state of the 16-state continuous time Markov chain \( \{X_t\} \), with transition rate matrix \( Q \) and arrival rate matrix \( \Lambda = \text{diag} [\lambda_1, \lambda_2, ..., \lambda_{16}] \), at the time \( t \) given the observation history \( J_t \). Namely,

\[
\hat{X}_t = \mathbb{E}\{X_t | J_t\}, \tag{4.2}
\]
where $E\{.\}$ denotes the expectation operator. This Bayesian estimation is essentially a continuous-time Hidden Markov Model (HMM), which can be represented in Martingale formulation as:

$$X_t = X_0 + \int_0^t Q' X_r d\tau + M_t,$$

(4.3)

where $M_t$ is a martingale with respect to the filtration generated by $X$. For a brief introduction of the concept of martingale theory see [36, Appendix B]. Then

$$dX_t = Q' X_t dt + dM_t.$$ 

(4.4)

Given the observation history $\mathcal{N}_t$, the estimation $\hat{X}_t$ (4.2) is obtained via the so called MMPP filter as follows:

$$E\{X_t|\mathcal{N}_t\} = \frac{q_t}{\sum_{i=1}^{16} q_t(i)}$$

(4.5)

where the un-normalized filtered density $q_t$ (which is a 16 dimensional vector with non-negative elements) is computed by the following Zakai equation [36]:

$$dq_t = Q' q_t dt + (\Lambda - I) q_t d\tau$$

(4.6)

where $n_t = N_t - t$.

$$q_t = q_0 + \int_0^t Q' q_r d\tau + (\Lambda - I) q_r d\tau$$

(4.7)

Note that the above integral involving $d\tau$ is Stieltjes integral. Recall $dn_t = dN_t - dt$ and $dN_t = 1$ if an IP packet arrivals at time $t$, and is zero otherwise. The derivation of the above MMPP filter equation (4.7) appears in [37][38].

As shown in Figure 4.2, let $t_i^{(k)}$, $i = 1, 2, ..., n(k)$ denote the packet arrival times of
Chapter 4. Traffic prediction in OBS network

MMPP $N_t$. Then (4.7) can be written as

$$q_t = q_0 + \int_0^t (Q' - \Lambda + I) q_t \, d\tau + (\Lambda - I) \sum_{\tau_i^{(k)} \leq \tau} q_{i^{(k)}}, \quad (4.8)$$

where $\tau_i^{(k)}$ denotes the time just before the IP packet arrival at time $\tau_i^{(k)}$. This leads to the following exact implementation: For $\tau_i^{(k)} \leq t \leq \tau_i^{(k+1)}$,

$$q_t = \exp \left[ (Q' - \Lambda + I)(t - \tau_i^{(k)}) \right] q_{i^{(k)}}. \quad (4.9)$$

That is, $q_t$ evolves deterministically between two successive IP packet arrivals. At the packet arrival time $t = \tau_i^{(k+1)}$, $q_{i^{(k+1)}}$ is updated as

$$q_{i^{(k+1)}} = \Lambda q_{i^{(k)}}, \quad (4.10)$$

Therefore, $q_{i^{(k+1)}}$ can be updated just at each packet arrival:

$$q_{i^{(k+1)}} = \Lambda \exp \left[ (Q' - \Lambda + I)(\tau_i^{(k+1)} - \tau_i^{(k)}) \right] q_{i^{(k)}} \quad (4.11)$$

Note $(\tau_i^{(k+1)} - \tau_i^{(k)})$ is the packet interarrival time of the $k$th burst. From this equation, it also follows that the optimal predicted state estimate of the 16-state Markov chain $X_t$ given the observation of MMPP $N_t$ up to time $\tau$, $\tau \leq t$ can be computed as:

$$\hat{X}_t = \mathbb{E}\{X_t|N_t\} = \frac{q_{t|\tau}}{\sum_{i=1}^{16} q_{t|i}}, \quad (4.12)$$

$$q_{t|\tau} = \Lambda \exp \left[ (Q' - \Lambda + I)(t - \tau) \right] q_{\tau}. \quad (4.13)$$

Given the above MMPP filter (4.7) and the predictor (4.13), we can now derive the Bayesian predictor for the $(k+1)$th burst. Recall that our aim is to predict the $(k+1)$th
burst size at the time its first packet arrival $r_{1}^{(k+1)}$, since we set the prediction interval $\Delta$ as the burst assembly time $r_a$. We shall use the following representation for Eq. (3.20):

$$N_t = \int_0^t g'\hat{X}_s ds + m_t.$$  \hspace{1cm} (4.14)

Then the MMSE (conditional mean) predicted number of packets arriving in the interval $(r_{1}^{(k+1)}, r_{1}^{(k+1)} + \Delta]$ given the observation history $N_{r_{1}^{(k+1)}}$ is:

$$\hat{L}_{k+1} = E\{\int_{r_{1}^{(k+1)}}^{r_{1}^{(k+1)} + \Delta} g'X_t dt + dm_t|N_{r_{1}^{(k+1)}}\}$$  \hspace{1cm} (4.15)

$$= E\{\int_{r_{1}^{(k+1)}}^{r_{1}^{(k+1)} + \Delta} g'X_t dt|N_{r_{1}^{(k+1)}}\} + E\{m_{r_{1}^{(k+1)} + \Delta} - m_{r_{1}^{(k+1)}}|N_{r_{1}^{(k+1)}}\}$$  \hspace{1cm} (4.16)

$$= \int_{r_{1}^{(k+1)}}^{r_{1}^{(k+1)} + \Delta} g'X_t dt.$$  \hspace{1cm} (4.17)

$$= \int_{r_{1}^{(k+1)}}^{r_{1}^{(k+1)} + \Delta} g'\hat{X}_{r_{1}^{(k+1)}} dt.$$  \hspace{1cm} (4.18)

where the equality (4.17) follows the property of martingales stated in equation (3.21).

Finally, substitute $\hat{X}_{r_{1}^{(k+1)}}$ with Eq. (4.12) and (4.13) in Eq. (4.18), we can get the following Bayesian predictor for the $(k+1)$th burst size:

$$\hat{L}_{k+1} = g' \int_{r_{1}^{(k+1)}}^{r_{1}^{(k+1)} + \Delta} e^{(Q' - \Lambda + I)(t - r_{1}^{(k+1)})} dt \sum_{i=1}^{16} \frac{q_{r_{1}^{(k+1)}}(i)}{\sum_{i=1}^{16} q_{r_{1}^{(k+1)}}(i)}.$$  \hspace{1cm} (4.19)

In the OBS system, since this prediction interval $\Delta$ is referred to as burst assembly time, which is usually preconfigured as a system parameter at the network design stage, the integral of matrix exponential in Eq. (4.19) can be precomputed, while the update of $q_r$ involves a matrix vector multiplication of complexity $O(16^2)$. This predictor can be implemented numerically by suitable discretization.
However, in the case of a threshold-based mechanism is adopted for burst assembly, the burst is framed when the maximum burst size is reached. Therefore, the burst length is fixed while burst assembly time is varying. We can use the same prediction algorithm to predict the burst assembly time, and determine when to begin a reservation.

In order to facilitate the solution of Eq. (4.19), let

$$\eta = t - \tau^{(k+1)}_1.$$  

Then we have

$$\hat{L}_{k+1} = g' \int_0^{\Delta} e^{Q' \eta} d\eta \frac{q_{\tau^{(k+1)}_1}}{\sum_{i=1}^{16} q_{\tau^{(k+1)}_i}(t)}.$$  

(4.20)

If we define

$$\Phi = e^{Q' \eta},$$

$$\Gamma = \int_0^{\Delta} e^{Q' \eta} d\eta$$  

(4.21)

the matrix exponential approximated by \( \Phi \) series expansion,

$$\Phi = e^{Q' \eta} = I + Q' \eta + \frac{(Q' \eta)^2}{2!} + \frac{(Q' \eta)^3}{3!} + ...$$  

(4.22)

can also be written as:

$$\Phi = I + Q' \eta \Psi,$$  

(4.23)

where

$$\Psi = I + \frac{Q' \eta}{2!} + \frac{(Q' \eta)^2}{3!} + ...$$
Chapter 4. Traffic prediction in OBS network

1. Matrix $I \leftarrow \text{Identity}$
2. Matrix $\Psi \leftarrow I$
3. $k \leftarrow 25$; Comment: we are using $N = 25$ in (4.25).
4. If $k = 1$, go to step
5. Matrix $\Psi = I + \frac{Q\eta}{k}\Psi$
6. $k = k - 1$
7. Go to step 4
8. Matrix $\Gamma \leftarrow \Psi\eta$
9. Matrix $\Phi = I + Q\eta\Psi$

Table 4.1: Program logic to compute $\Phi$ and $\Gamma$ for simple case, eg. $N = 25$

The $\Gamma$ integral in (4.21) can be evaluated term by term to give

$$
\Gamma = \sum_{k=0}^{\infty} \frac{Q'^k\eta(k + 1)}{(k + 1)!}
$$

$$
= \sum_{k=0}^{\infty} \frac{(Q'\eta)^k}{(k + 1)!}\eta
= \Psi\eta
$$

(4.24)

We evaluate $\Psi$ by a series in the form

$$
\Psi \approx I + \frac{Q'\eta}{2}(I + \frac{Q'\eta}{3}(\cdots \frac{Q'\eta}{N-1}(I + \frac{Q'\eta}{N})\cdots)),
$$

(4.25)

which has better numerical properties than the direct series of powers. We then find $\Gamma$ from (4.24) and $\Phi$ from (4.23). By comparing to the direct computation of the matrix exponential, we choose $N = 25$ here as an approximation. Then the program logic for computation of $\Phi$ and $\Gamma$ is given in Table 4.1.

Due to the imperfection of a predictor, an estimated length may turn out to be smaller or larger than the actual burst duration. A smaller burst length prediction will result in insufficient reservation on the path holding time for the data burst. This will cause burst drop at the intermediate node on the path in the core network. So, we compare
the predicted value and the actual value at the edge node when the burst assembly is finished. When the smaller prediction happens, it requires the BHP to be re-transmitted after the burst assembly finishes, thus degrading the latency reduction performance.
Chapter 5

Performance Analysis and Simulation Results

In this chapter we present several simulations to illustrate the Bayesian MMPP predictor and its effect on the latency reduction and burst blocking probability of the OBS network. The input traffic is assumed to be self-similar with LRD properties. The simulation platform is OPNET.

5.1 Model Setup

This section describes how an OBS network model has been implemented in OPNET Modeler 9.1. In general, section 5.1.1 briefly describes our network methodology; in sections 5.1.2, we give a detailed introduction on how to develop our MMPP traffic models in OPNET; in section 5.1.3 and 5.1.4 we focus on the functionality and system parameters set up on the OBS edge node and core node, separately.

5.1.1 Optical network architecture

We use the optical network architecture in Figure 5.1, which is similar to [39].
Chapter 5. Performance Analysis and Simulation Results

1. The network consists of a core part (OTN) and an external part (optical edge routers), where control channel and data channel are separated.

2. Core network (OTN) consists of a fully connected mesh of four optical cross connects (OXC), with full wavelength conversion.

3. Network edge routers are capable of aggregation and de-aggregation of IP packets.

4. The network supports two classes of traffic.

5.1.2 Traffic generator

The generator node must generate packets, process them, and send them on to the point-to-point transmitter. This can be modelled using a traffic source processor to generate packets, another processor to perform any necessary operations, and a point-to-point transmitter to transmit the packets on the point-to-point link. This node structure is shown in Figure 5.2, where the “src” module generates MMPP traffic and the “proc”
module specifies other information, such as destination address, QoS requirements etc. "xmt" is simply the point-to-point transmitter. For simplicity, the IP packet header contains only information needed in our experiment, as shown in Table 5.1.

Recall that in our simulation, the traffic model for each FEC is a 16-state MMPP process, which is mathematically computed by superposing four 2-state MMPPs in section 3.3.2. The structure of this MMPP traffic generator is shown in Figure 5.3. Simulation results validate that our 16-state MMPP model is good at modelling self-similar traffic in four to five time scales. Therefore the traffic generated from the above source processor has the property of long-range dependence (LRD) in four to five time scales.

5.1.3 **Edge router**

The main role of edge routers in the OBS network is to provide packet transmissions between the optical domain and the electrical domain. There are two types of edge routers, i.e., ingress and egress routers. The one transmitting packets from the electrical domain to the optical domain (OTN) is referred to as ingress router, and vice versa. Edge routers also implement OBS MAC layer functions between IP and optical layer.
Figure 5.3: MMPP traffic generator – the aim of this figure is to illustrate the transactions between this 16-state MMPP

- Key functions of OBS MAC layer at the ingress router are:

1. Classify the incoming IP packets based on their destinations and QoS class into different FEC classes. Later, optical burst will be generated from each FEC queue. The optical burst structure is shown in Figure 5.4.

2. For different classes traffic, service differentiation is provided. For high-priority traffic, a predictor is inserted to predict the burst length before it has been fully assembled. In this case, the offset time $\tau_0$ between BHP and the data payload is equal to the burst assembly time $\tau_a$. Then BHP contains the above information and routing information (label) is launched, and will be sent out directly after it has been generated. For low-priority traffic, the BHP is generated after the burst assembly is finished, so the BHP contains the exact knowledge of
Figure 5.4: OBS burst structure

Table 5.2: Burst Header Packet (BHP) format

<table>
<thead>
<tr>
<th>field name</th>
<th>type</th>
<th>size</th>
<th>comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>label</td>
<td>integer</td>
<td>32 bits</td>
<td>MPLS routing information</td>
</tr>
<tr>
<td>wave_id</td>
<td>integer</td>
<td>8 bits</td>
<td>for output wavelength reservation</td>
</tr>
<tr>
<td>class</td>
<td>integer</td>
<td>4 bits</td>
<td>setting FEC class for Qos requirement</td>
</tr>
<tr>
<td>offset_time</td>
<td>integer</td>
<td>32 bits</td>
<td>offset time between BHP and burst</td>
</tr>
<tr>
<td>num_pk</td>
<td>integer</td>
<td>8 bits</td>
<td>number of packet of a burst</td>
</tr>
<tr>
<td>burst_size</td>
<td>integer</td>
<td>32 bits</td>
<td>actual burst size</td>
</tr>
</tbody>
</table>

the burst length. However, the assembled data burst has to be queued in the ingress for a preconfigured offset time \( \tau_0 \), which is set to the total path set up time in the core network. A BHP format is shown in Table 5.2.

3. Frame the burst after the offset time has elapsed and send the burst into the optical layer. A burst is set to be at least several kilobytes long in order to be comparable with the real OEO time needed for its header to set up a switching path, which is presumed to be in the range of microseconds. Usually a burst consists of several tens to hundreds of IP packets and the assembling time is also in the range of hundreds of microseconds (\( \mu s \)) to several milliseconds (\( ms \)).

4. Support two interfaces for input and output on the OTN side as well as the terminal workstation side.

5. The ingress router processor has a switching table, for example, Table 5.3,
which is used to forward the optical bursts on a particular output stream on an output port.

<table>
<thead>
<tr>
<th>Dest.address</th>
<th>Dest.egress</th>
<th>Dest.port</th>
<th>Dest.wavelength</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

Table 5.3: Edge router switching table

The node model of an ingress router is depicted in Figure 5.5, where the “aggregate” module performs the above functions, and the control channel is separated from those data channels at the electrical to optical interface. It also shows that the ingress node supports four data channels (wavelengths) at each output port.

Figure 5.5: Ingress node model (pr_0 and pr_1 are imports; tx0_BHP and tx1_BHP are outports for BHP; pt_0 and pt_1 are outports for data burst, each with 4 wavelengths)

- Key functions of OBS MAC layer at the egress router are:
1. Deframe the bursts and extract IP packets from them.

2. Look up the final destination for all the workstations connected to it.

3. The egress router processor also has a global forwarding table, which is used to look up the final destinations directly connected to the egress router.

<table>
<thead>
<tr>
<th>Egress address</th>
<th>Dest.address</th>
<th>Dest.port</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 5.4: Edge router forwarding table

5.1.4 Core Router (OXC)

A simplified architecture of a core node with 4 input/output links is represented in Figure 5.6. There are 8 inputs and 8 outputs, each represented by a point-to-point receiver and transmitter, respectively. Four of the receivers and transmitters have four channels, which represent 4 data WDM channels. The other receivers and transmitters are single channel and represent the BHP channels on each link. Thus, each combination of BHP transmitter and receiver, and 4-channel data receiver and transmitter represents the connection to a fibre link to an edge node or other intermediate core node.

All of the receiver/transmitter components are connected to a central process model SCU (switch control unit) via packet streams. The SCU is responsible for:

1. reading switching information from a precomputed MPLS-type label information table (LIB)

2. swapping input and output labels
Chapter 5. Performance Analysis and Simulation Results

3. calculating new offset times

4. performing wavelength conversions

5. making resource reservations for corresponding data bursts

6. reassembling BHP with new necessary information

7. relaying optical bursts to output ports according to the switching table

8. implementing optical output buffers needed for each outgoing burst

In the process model, decisions are made depending on whether a BHP or a data burst is received. When a BHP is received, all of its information is extracted to the SCU. Here
the control packet is transformed to the electrical domain. In the electrical domain, the following actions take place:

- The label in the BHP is used to point to the data burst forwarding information in the LIB, such as the output interface and Qos information.

- Information in the BHP about burst length and the offset time of the data burst is used in addition to the forwarding information derived from the LIB. In particular, the latter is used to determine the mapping from the incoming fiber and wavelength to the outgoing fiber and wavelength. To be able to forward successive data bursts of the same connection (LSP) on different wavelengths in a given fiber, we propose that the label specify only incoming-fiber-to-outgoing-fiber mapping, while the information about the wavelength be appended to the outgoing label at every hop.

- The SCU determines burst outgoing fiber by looking up its precomputed LIB, and makes wavelength reservation on designated output port, which supports full wavelength conversion. Then the cross-connect is set up to switch the data burst corresponding to that control packet in the all-optical domain.

- By recalculating a new offset time, the BHP is reassembled with new necessary information and undergoes label swapping (and wavelength information appending) and is forwarded on the dedicated control channel of the outgoing fiber as indicated by the LIB. Thus the OEO transformation is finished.

If, on the other hand, a data burst is received, a check is made with the SCU to extract the next hop of the burst. The data burst is transmitted transparently in the pure optical domain. Table 5.5 is an example of a label information table for label switching.

In this simulation, we use one-way reservation scheme. That is, the sender of a burst
does not wait for a positive acknowledgment (ACK) of its reservation request. The advantage of one-way reservation is higher efficiency, as there is no overhead caused by the propagation delay. This scheme is appropriate because OBS will most likely be implemented in long-haul networks and therefore the one-way reservation will significantly decrease the time needed to establish a connection. An example may illustrate this. The transmission time of a 100KB burst on a 10Gbps link is 80μs while the propagation delay over a distance of 200km (which is not long in a backbone network) is typically about 1 ms.

### 5.1.5 Buffer at routers

- Electronic buffers at each ingress router for packets aggregation purpose are represented by a single server FIFO queue per FEC.

- Optical buffers (FDLs) are fixed for each label and should be allocated among all classes. A group of FDLs with variable length can act as the FIFO queue.

Table 5.5: Information Base (LIB) at Core Node

<table>
<thead>
<tr>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port</td>
<td>Wavelength</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>2</td>
</tr>
<tr>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

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Chapter 5. Performance Analysis and Simulation Results
Chapter 5. Performance Analysis and Simulation Results

5.2 Simulation Experiments and Results

In this section, we first compare the LMS-based linear predictor with our proposed MMPP Bayesian predictor based on the prediction quality. We then show the performance improvement in terms of ETE delay and burst blocking probability when applying our MMPP predictor.

5.2.1 Assumptions

- All sources of data from upper clients are assumed to be self-similar traffic. A superposition of four 2-state MMPPs are used in this simulation to represent the aggregated self-similar traffic of each FEC at the OBS ingress nodes.
- IP Packet size is fixed in each scenario.
- Packets with the same destination address and QoS requirement belong to one Forward Equivalent Class (FEC).
- Assume MPLS is used to set up a lightpath and to reserve bandwidth for each source-destination pair (SD). Each Label Switching Path (LSP) is identified with a label and can be transmitted via more than one channel.
- Full wavelength conversion is assumed at each core node.
- Optical buffers are allocated on a per-class and per-label basis, according to the incoming traffic intensity and priority.
- Traffic from different sources may share the same label, provided they are destined for the same egress.
5.2.2 Prediction performance improvement

We first study the LRD traffic prediction performance by comparing two prediction methods: simple LMS-based predictor [7] and our proposed MMPP Bayesian predictor. Figure 5.7 shows the probability density of the prediction error for both our proposed MMPP Bayesian predictor and the traditional LMS-based linear predictive filter (LPF). It is obvious that the LMS-based LPF has larger prediction error variance in comparison with our MMPP Bayesian predictor. Recall that the Bayesian estimation algorithm is optimal in the sense of minimum variance. Note that the error in this figure is un-normalized.

![Probability Density of Prediction Error](image)

Figure 5.7: PDF of prediction error (in bits)
Let $\hat{L}_{k+1}$ be the predicted burst length and $L_{k+1}$ be the actual burst length. The performance is further evaluated by the following two criteria.

First is the prediction interval, which refers to how far into the future the traffic can be predicted with confidence. Define the normalized Δ-step prediction error as:

$$E(\Delta) = \frac{|\hat{L}_{k+1} - L_{k+1}|}{L_{k+1}}.$$  \hspace{1cm} (5.1)

Assume that confident prediction requires that $E(\Delta)$ should not exceed a percentage $\varepsilon$ (e.g. 20%) with a probability $P_\varepsilon$ (e.g. 0.01), where $(P_\varepsilon, \varepsilon)$ is the specified prediction confidence interval. Therefore, a large prediction confidence interval implies good traffic predictability.

Now, if we define $P_\varepsilon = P\{E > \varepsilon\}$, we can compare the performance of two predictors on how confidently and how far they can predict the future. Figure 5.8 compares the simulation results of $P_\varepsilon$ vs. prediction interval $\Delta$.

The simulation results show that $P_\varepsilon$ of MMPP predictor grows much slower then LPF when the prediction interval $\Delta$ increases. Furthermore, the MMPP predictor can bound the confidence pair $(P_\varepsilon, \varepsilon)$ as (0.012, 10%) and (0.008, 20%) when $\Delta$ approaches 3ms, which is usually sufficient for assembling optical bursts.

Signal-to-Noise Ratio (SNR) is another criterion for evaluating the prediction performance, which refers to the accuracy of a prediction algorithm. Now denote SNR as:

$$SNR(\Delta) = E[L_{k+1}^2]/\sigma^2_\Delta, \quad \sigma^2_\Delta = E[(\hat{L}_{k+1} - L_{k+1})^2],$$  \hspace{1cm} (5.2)

where $\Delta$ is the prediction interval, and $\sigma^2_\Delta$ is the Δ-step prediction variance. The larger SNR implies the better prediction accuracy. In our thesis, we use the inverse of SNR, i.e.,
SNR\(^{-1}\) for comparing the above two prediction methods. Namely,

\[
SNR^{-1} = \frac{E[(\hat{L}_{k+1} - L_{k+1})^2]}{E[L_{k+1}^2]}.
\] (5.3)

SNR\(^{-1}\) is usually influenced by the parameters such as burst assembly duration \(\tau_a\), i.e., prediction interval, and traffic load \(\rho\), since increasing traffic load implies increasing of hurst parameter \(H\) (the traffic bursty degree). We conduct a set of simulations by tracing the dependence of \(SNR^{-1}\) on the above two parameters, respectively.

Figure 5.9 shows the effect of burst assembly duration. In this scenario, we set the other parameters as \(\rho = 25\%\) and \(H = 0.75\), since the bandwidth utilization of today's optical network is typically under 25%.

Figure 5.10 compares \(SNR^{-1}\) with the variation of traffic load in the core network.
In this scenario, we consider small assembly time ($\tau_a = 200\mu s$) and large assembly time ($\tau_a = 2ms$) cases, respectively.

Again, smaller SNR$^{-1}$ implies better prediction accuracy. For our MMPP predictor, Figure 5.9 shows that (SNR$^{-1} \leq 1\%$) is achieved when the burst assembly time $\tau_a$ is between $100\mu s$ to $1ms$. Meanwhile, as $\tau_a$ grows to $3ms$, the SNR$^{-1}$ is kept within $2\%$. On the other hand, the SNR$^{-1}$ of the LMS-based predictor increases dramatically when $\tau_a$ grows from tens of microsecond to the time scale of millisecond. This is because the traffic behaves long-range dependence over several time scales while the burst is in assembling. It is inherent in the fact that LMS algorithm converges and adapts to sudden changes is slower. In this scenario, it also yields the average accuracy improvement of MMPP predictor over LMS predictor as 87%. From Figure 5.10 we observe that SNR$^{-1}$
of MMPP predictor almost remains constant while increasing traffic load. This is because the MMPP predictor has the knowledge of incoming traffic structure, which is independent of traffic load. However, the LMS-based predictor behaves different when feeding traffic becomes heavier. In the case of small assembly time applied, SNR$^{-1}$ is decreasing while traffic load increasing. This result indicates that when many source traffic aggregated, the aggregated traffic turns out to be smoother in very short time scales. Now we look at larger time scales, i.e., the case of large assembly time applied. SNR$^{-1}$ is increasing with the traffic load since the traffic bursty degree also grows, which can not be shaped away at this burstification range.
5.2.3 BHP pre-transmission success probability

In our system, a successful BHP pre-transmission means sufficient bandwidth is reserved before burst data arrives at each intermediate core node. That is, a smaller prediction of burst length:

\[ e(k + 1) = (L_{k+1} - \hat{L}_{k+1}) \leq 0 \] (5.4)

will result in an insufficient reservation of the path-holding time for the data burst. This requires the control header to be retransmitted after the burst assembly finishes, thus degrading the latency reduction performance.

A common method for correcting this problem is to add a small correction margin for the predicted value. Instead of making the reservation length the predicted value \( L_{k+1} \), we define the reservation length as:

\[ L_r(k + 1) = \hat{L}_{k+1} + \delta \] (5.5)

where \( \delta \) is a small margin of correction. Let \( P_s \) denote the probability of success BHP pre-transmission:

\[ P_s = P\{e(k + 1) < \alpha\}, \quad \alpha = \max\{\sigma, \delta\} \] (5.6)

where \( \sigma \) is the variance of prediction error \( e(k + 1) \). Here the constraint \( \alpha \) indicates that the prediction error overhead is limited in our system. Figure 5.11 shows the BHP pre-transmission success probability versus burst assembly time \( \tau_a \). Since \( P_s \) depends largely on the correction margin \( \delta \), we also compare the results of \( P_s \) with \( \delta \) variations.

Based on the central limited theorem, the prediction error \( e(k + 1) \) is assumed to be normal, with zero mean and variance \( \sigma^2 \). For all normal distributions, the density function is symmetric about its mean value. About 68% of the area under the curve is within one
standard deviation of the mean, 95.5% within two standard deviations, and 99.7% within three standard deviations. Therefore, we only need to consider the correction margin:

\[ \delta = n\sigma, \quad n \in [0, 3]. \]  

(5.7)

From Figure 5.11, we notice that the BHP pre-transmission success probability could be highly improved with a small amount of correction value.

![Figure 5.11: Comparison of $P_s$ versus burst assembly time $\tau_a$](image)

5.2.4 Latency reduction improvement

Now we can study how prediction accuracy and efficiency influence the system end-to-end (ETE) delay at edge routers. We consider first low-priority traffic without burst length
prediction in the OBS edge routers. In this scenario, we use a one-way reservation protocol such as JET [19]. At the edge node, packets with the same FEC class are aggregated into a container. When assembly time is over, i.e., when $\tau_a$ expires, the BHP is made and sent out to the core network immediately, while the container is framed to a burst and stored in the edge node, and will be sent when the determined offset time expires. The ETE delay

$$D_n = \frac{1}{2} \tau_a + \tau_0 + \tau_i, \quad (5.8)$$

where $\tau_i$ is the total transmission time of data burst throughout the designated LSP. The offset time $\tau_0$ is set to be the total OEO time + switching setup time at each intermediate node through the designated LSP in the core network.

For high-priority traffic with burst length prediction, we can dynamically reserve sufficient bandwidth at the OBS core network. In this scenario, we also use a one-way
reservation protocol, such as FRR, proposed in [7], which is a variation of JET that focuses on delay deduction. The edge nodes determine all the routing and reservation information before the entire burst is assembled, then make and send the control header (BHP) immediately, while the burst is still being assembled. The burst assembly will be finished when the preconfigured assembly timer \( \tau_a \) expires. However, the knowledge of the burst length has been predicted at the arrival of the first packet of the burst. Simulation results show that the latency deduction value achieves the maximum when \( \tau_o \) is set to the same as \( \tau_a \) [7]. It is quite straightforward that the assembly time is saved when \( \tau_o = \tau_a \), as shown in Figure 5.12.

Therefore, with prediction, the ETE delay:

\[
D_p = \frac{1}{2} \tau_a \cdot P_s + \left( \frac{1}{2} \tau_a + \tau_o \right) \cdot (1 - P_s) + \tau_t.
\]  

(5.9)

For \( \tau_o = \tau_a \), Eq. 5.9 can be rewritten as:

\[
D_p = \left( \frac{3}{2} - P_s \right) \cdot \tau_a + \tau_t.
\]  

(5.10)

In the OBS network, we observe that the bandwidth in the core network (OC192 or more) is much higher than that in the edge network (OC3 to OC48). The time for assembling a burst, which is usually in the hundreds of microseconds, and is comparable with the OEO time. The transmission time in the core network is usually in the time scale of several microseconds, which could be negligible to the assembling time. When pre-transmission probability \( P_s \) achieves 1, the system end-to-end delay is \( D_p = \frac{1}{2} \tau_a \).

The latency improvement \( (\eta) \) could be expressed by

\[
\eta = 1 - \frac{D_p}{D_n} = 1 - \frac{1}{3} P_s
\]  

(5.11)
If the burst length could be predicted precisely such that the pre-transmission of the BHP succeeds with a high probability ($P_s \rightarrow 100\%$), the edge could reduce the latency by 66% when $\tau_0 = \tau_a$, and transmission time is negligible.

![ETE delay with/without prediction](image)

**Figure 5.13: Comparison of ETE delay with/without Prediction**

In our simulation, we calculate the actual ETE delay by also considering the transmission time through the light path, since the transmission time should not be ignored in a complicated network. An example may illustrate this. The transmission time of a 100KB burst on a 10 Gbps link is 80$\mu$s. As shown in our fully meshed network structure, optical burst usually undergoes several hops in the core network. So the accumulated transmission time might be comparable to burst assembly time. Figure 5.13 compared the overall ETE delay with no prediction, linear prediction, and our MMPP prediction. The simulation result shows that our proposed MMPP predictor can improve the performance of ETE delay about 30% ~ 35% compared to a traditional linear predictor, with a relatively larger
prediction interval, and around 50% compared to the situation without predictor.

5.2.5 Effect on Burst blocking probability

![Comparison of burst loss probability](image)

Figure 5.14: Comparison of burst blocking probability with different predictor

In the OBS system with its one-way reservation scheme, if the requested bandwidth is not available, the burst is said to be blocked and dropped. As a burst may contain several user packets, the loss of a burst is critical in OBS networks, which may incur severe problems at upper layers, e.g., TCP packets out of sequence. The performance of OBS networks in terms of burst blocking probability has been studied extensively [40][41] using either simulation or simple analytical models. Burst blocking probability is influenced mainly by traffic load, traffic characteristics, and number of wavelengths, as discussed in [42].
Figure 5.14 compares two predictors for the following criteria: burst loss ratio, also called burst blocking probability. In our simulation, we mainly consider the LRD traffic with $H = 0.75$ and our system support full wavelength conversion for only 4 wavelengths. So the blocking probability is higher in comparison to more wavelengths cases. The simulation results validate that, with a more precise prediction of the burst length, the burst loss ratio can be highly decreased.
Chapter 6

Conclusion and Future Work

6.1 Conclusion

This thesis studies optical burst switched (OBS) networks, Internet IP traffic modeling at the OBS edge networks, and on-line burst size prediction for dynamic bandwidth reservations.

- First, this thesis presents a detailed analytical model for the burst shaping (assembly), scheduling and wavelength reservation schemes for OBS networks. Though there has already been research on this subject, the models proposed in this thesis are more viable and valid for general burst length and offset length distributions. QoS differentiation is facilitated at network edges.

- In the second part of the thesis, special attention has been paid on traffic modeling for self-similar Internet traffic with long-range dependence (LRD) properties. The incoming IP traffic at OBS ingress nodes is approximated by using the superposition of several MMPPs. We find that, under reasonable assumptions regarding the system parameters of burst assembly, i.e., burst assembly time and OEO time-scales in optical switch and electronic hardware, the performance of our traffic model using the superposition of four 2-state MMPPs seems to get close to that of more
Chapter 6. Conclusion and Future Work

complicated FBm and FGn. That is, it is practical sufficient to model LRD traffic properties in several time scales.

- Last but not least, a recursive Bayesian (optimal) filtering/prediction method is proposed to predict optical burst length at the OBS ingress node. For IP traffic approximated by a N-state MMPP, the computational complexity is $O(N^2)$. By this burst length prediction, burst control header (BHP) can be transmitted down to the core network before burst assembly is completed, thus greatly reducing burst assembly delay at the edge node and further facilitating the service differentiation based on QoS requirements among different classes. Simulation studies are presented to illustrate the performance of our proposed predictor in comparison to earlier proposed LMS-based linear predictive filter. Theoretical analysis and simulations exhibit encouraging results. The performance study indicates that, the recursive Bayesian predictor delivers excellent forecasting performance for the self-similar traffic which best models the Internet traffic, and is proved to be practical in reducing the data burst delay at network ingress routers of an OBS system.

6.2 Extensions

Several issues remain open and are worthy of further investigation to generalize our prediction scheme and to unleash the potential of QoS provisioning for the OBS system. For example, the proposed Bayesian predictor is an on-line optimal (minimum-variance) predictive filter, which provides an optimization of the burst-length prediction. However, there are two disadvantages of this estimation scheme, i.e., the “curse of computational cost” and the “curse of traffic model”. The algorithm involves matrix multiplication, which results in the computational effort being of the order $O(N^2)$, which can be large for
large $N$. Recently, some reduced-complexity filtering algorithms have been proposed [43] to solve this problem. In this thesis, the Bayesian prediction algorithm is derived based on a MMPP traffic model, assuming full knowledge of the MMPP traffic structure. As we stated in Chapter 1, we skipped the step 2, i.e., parameter estimation. The expectation-maximization (EM) algorithm is a popular off-line locally convergent scheme for obtaining maximum likelihood estimates of the HMM parameters. Future research may focus on online Bayesian prediction of MMPP models with unknown transition matrix.
Glossary

Operators

diag(·) diagonal matrix with diagonal entries of vector argument
\( \mathbb{E}\{ \cdot \} \) expectation
\( \mathbb{P}\{ \cdot \} \) probability
\( \oplus \) Kronecker’s sum
\( \cdot ^\prime \) transpose
\( \langle \cdot, \cdot \rangle \) scalar product
\( \| \cdot \|^2 \) the Frobenius norm

Other Functions

\( \exp(\cdot) \) exponential function
\( \ln(\cdot) \) logarithm to base e
\( \log_{10}(\cdot) \) logarithm to base 10

Acronyms

AONs All-optical Networks
AR Advanced Reservation
ARIMA Auto Regressive Integrated Moving Average
BCU Burstification Control Unit
BHP Burst Header Packet
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>CLT</td>
<td>Central Limit Theorem</td>
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<tr>
<td>DR</td>
<td>Delayed Reservation</td>
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<tr>
<td>ETE</td>
<td>End-to-End</td>
</tr>
<tr>
<td>FARIMA</td>
<td>Fractal Auto Regressive Integrated Moving Average</td>
</tr>
<tr>
<td>FEC</td>
<td>Forward Equivalence Class</td>
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<tr>
<td>FDL</td>
<td>Fiber Delay Line</td>
</tr>
<tr>
<td>fBm</td>
<td>Fractional Brownian Motion</td>
</tr>
<tr>
<td>fGn</td>
<td>Fractional Gaussian Noise</td>
</tr>
<tr>
<td>IPP</td>
<td>Interrupted Poisson Process</td>
</tr>
<tr>
<td>JET</td>
<td>Just-Enough-Time</td>
</tr>
<tr>
<td>JIT</td>
<td>Just-In-Time</td>
</tr>
<tr>
<td>HMM</td>
<td>Hidden Markov Model</td>
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<tr>
<td>MMPP</td>
<td>Markov Modulated Poisson Process</td>
</tr>
<tr>
<td>MMSE</td>
<td>Minimum Mean Square Error</td>
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<tr>
<td>MPLS</td>
<td>Multi-Protocol Label Switching</td>
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<tr>
<td>LMS</td>
<td>Least Mean Square</td>
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<tr>
<td>LPF</td>
<td>Linear Prediction Filter</td>
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<tr>
<td>LRD</td>
<td>Long Range Dependence</td>
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<tr>
<td>LSP</td>
<td>Label Switched Path</td>
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<tr>
<td>OBS</td>
<td>Optical Burst Switching</td>
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<tr>
<td>OCS</td>
<td>Optical Circuit Switching</td>
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<tr>
<td>OEO</td>
<td>optical-electrical-optical</td>
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<tr>
<td>OPS</td>
<td>Optical Packet Switching</td>
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<tr>
<td>OTN</td>
<td>Optical Transport Network</td>
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<tr>
<td>OXCs</td>
<td>Optical Cross Connects</td>
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<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>SCU</td>
<td>Switch Control Unit</td>
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<tr>
<td>SNR</td>
<td>Signal-to-Noise Ratio</td>
</tr>
<tr>
<td>SRD</td>
<td>Short Range Dependence</td>
</tr>
<tr>
<td>WDM</td>
<td>Wavelength Division Multiplexing</td>
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<tr>
<td>WRONs</td>
<td>Wavelength-Routed Optical Networks</td>
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