REVENUE FOCUSED SEMI-PROTECTION FOR VOD SERVICE IN COST-EFFECTIVE DWDM NETWORKS

by

Kaiyan Jin
B.Sc., Harbin Engineering University, 2003

A PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

In the School
of
Computing Science

© Kaiyan Jin   2009

SIMON FRASER UNIVERSITY

Spring 2009

APPROVAL

Name: **Kaiyan Jin**

Degree: **Master of Science**

Title of Project: **Revenue Focused Semi-protection for VOD Service in Cost-effective DWDM Networks**

Examining Committee:

            Chair: **Dr. Dirk Beyer**
Assistant Professor, Computing Science

_____

Dr. Joseph G. Peters
Senior Supervisor
Professor, Computing Science

_____

Dr. Qianping Gu
Supervisor
Professor, Computing Science

_____

Dr. Mohamed M. Hefeeda
SFU Examiner
Assistant Professor, Computing Science

Date Defended/Approved: _____

SFU SIMON FRASER UNIVERSITY
LIBRARY

Declaration of
Partial Copyright Licence

ABSTRACT

Dense Wavelength Division Multiplexing (DWDM) technology is an important innovation to enable the network operators to utilize their optical networks efficiently. By multiplexing more wavelengths into one fiber, the data transmission rate of a fiber in DWDM networks is dramatically increased up to Terabits per second (Tbps). However, network operators are still struggling with the bandwidth shortage problems due to the explosion of data transmission demands, especially the transmission of video content. In this project, we present a survey of the research on cost-effective DWDM networks in terms of the routing and wavelength assignment (RWA) and traffic grooming problems. In addition, we extend a revenue focused semi-protection scheme, which uses the failure statistics, revenue statistics, and bandwidth statistics of VOD service to solve bandwidth shortage problems in DWDM ring networks. Our goal is to provide network operators with guidelines on the design or upgrade of their DWDM networks.

Keywords: DWDM, RWA, traffic grooming, VOD, revenue focused semi-protection, linear programming (LP), statistics.

ACKNOWLEDGEMENTS

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

GLOSSARY

ADM	Add/Drop Multiplexer
ATM	Asynchronous Transfer Mode
BLSR	Bidirectional Line Switched Ring
DWDM	Dense Wavelength Division Multiplexing
FDM	Frequency Division Multiplexing
HD	High Definition
OADM	Optical Add/Drop Multiplexer
RWA	Routing and Wavelength Assignment
SADM	SONET Add/Drop Multiplexer
SD	Standard Definition
SDH	Synchronous Digital Hierarchy
SONET	Synchronous Optical Network
TDM	Time Division Multiplexing
UPSR	Unidirectional Path Switched Ring
VOD	Video on Demand
WDM	Wavelength Division Multiplexing

NOTATION

c Class c customers categorized by revenue rate generated

f The number of interruptions a customer has experienced

F The total number of failures occurring in the operation period

$r(c)$ The revenue rate generated by a class c customer

revenue-ratio   The ratio between the revenue rates of the three classes of customers

$b(c)$ The bandwidth required for each class c customer

T_t The time right before the tth failure happens in the operation period $[\,T_0, T_{F+1}]$

$(c, f, t) - customers$ The group of class c customers at time T_t who have experienced f interruptions

$N(c, f, t)$ The number of (c, f, t)-*customers*

$n(c, f, t)$ The traffic load caused by the (c, f, t)-*customers*

$O(c)$ The number of new (c)-*customers*

$o(c)$ The traffic load caused by the new (c)-*customers*

$D(c, f, t)$ The number of dropped (c, f, t)-*customers* when the tth failure happens

$d(c, f, t)$ The amount of dropped traffic load of (c, f, t)-*customers* when the tth failure happens

triple-ratio   The ratio of the number of initial (c)-*customers*, denoted $N(0,0,0) : N(1,0,0) : N(2,0,0) = x : y : z$

ratio(c)   The initial ratio of the number of (c)-*customers* to the number of $(c+1)$-*customers*

$pw(c)$ The probability of (c)-*customers* watching a VOD program

$pun(c, f)$ The probability of a (c, f)-*customer* unsubscribing from the service if the customer experiences another failure

$w(c, f)$ The priority value of a (c, f)-*customer*

L The capacity of one link in the ring

1. INTRODUCTION

Dense Wavelength Division Multiplexing (DWDM), as an evolution of the conventional Wavelength Division Multiplexing (WDM), enables the network operators to utilize their existing optical network bandwidth efficiently. By multiplexing more wavelengths in a fiber, the data transmission rate in a fiber can be increased to over 10Tbps. For example, up to 14Tbps bandwidth in a fiber has been achieved in the laboratory [1] and up to 160 wavelength channels per fiber are in operation today [2].

On the other hand, the explosive growth of data transmission demands results in bandwidth shortage problems for network operators. The fast increasing video content service demands are the major causes, such as various TV programs, Video-on-Demand (VOD) services, and video conferences over networks. In addition, to provide reliable services, network protection schemes are applied, which requires extra bandwidth reserved in the event of network failures. Unidirectional Path Switched Ring (UPSR) and Bidirectional Line Switched Ring (BLSR), the two typical protections in SONET ring networks, require extra free bandwidth that is the same as the bandwidth of the working fibers. The reserved bandwidth works as a backup and enables full protection. Traditionally, network operators might have forecast the bandwidth growth and overbuilt their networks for long-term designs when they planned to set up their networks. However, almost all operators' predictions have failed to catch up with

the fast growing speed of video content service demands. To solve this problem, network operators have begun to consider the possibility of short-term or long-term upgrade plans to increase the bandwidth of their existing networks.

Generally speaking, there are two alternative upgrade plans to meet the growing bandwidth requirements.

First, network operators can choose to lay more optical cables to increase the total capacity. Although the price of optical cables is much cheaper than other transmission media (e.g., copper cables, measured by the price per unit bandwidth), this is still a costly option, considering all the expenses involved including labour and maintenance cost, conduit lease, new connection components, and the cable itself.

The other plan for network operators is to apply new technologies to utilize their existing networks efficiently without laying down additional fibers. DWDM networks make this possible and have been proved to be more cost-effective than the first plan. The technology of DWDM efficiently utilizes the bandwidth of a fiber by supporting multiple wavelengths transmitted simultaneously in one fiber. However, in order to multiplex more wavelengths into one fiber, more powerful and signal-sensitive transmission modules (primarily wavelength converters and add/drop multiplexers (ADMs)) are required to identify any two close wavelengths, which incurs high additional costs. Optical ADMs (OADMs) and SONET ADMs (SADMs) are the two major types of multiplexers in SONET networks. To build cost-effective DWDM networks, the key challenge is to maximize the efficiency of existing equipment and fibers at minimum deployment

2

cost. The routing and wavelength assignment (RWA) problem and the traffic grooming problem are the two main problems that must be solved to find optimal solutions in DWDM networks. The objective of the RWA problem is to find the communication paths for given connection requests and to assign paths wavelengths so that the number of required wavelengths is minimized. The objective of the traffic grooming problem is to realize the given connection requests by minimizing the use of SADMs in SONET networks. We will focus on these two problems and illustrate more details later in our project.

Either one of the above plans can be applied as a long-term upgrade design to increase the bandwidth of networks and accommodate the continuously growing bandwidth demand.

Nonetheless, with or without protection, both plans mentioned above require a certain amount of financial investment for network upgrade and deployment. Network operators who cannot afford such investment in the near future can consider another option to maximize the utilization of their existing networks without adding extra cost and losing revenue from network failures: a revenue focused semi-protection scheme proposed and studied in this project. Different from other protection schemes that require more reserved bandwidth to protect the network connections in the event of a failure, our revenue focused semi-protection scheme uses any free bandwidth in the working link to protect the selected network connections in the failed link and focuses on minimizing the revenue loss. Moreover, the revenue focused semi-protection scheme incurs no

extra hardware upgrade cost in DWDM networks in contrast to solutions of RWA and traffic grooming problems.

This project aims at solving the bandwidth shortage problem for a cost-effective network by considering using a revenue focused semi-protection scheme in DWDM networks. The solution proposed in this project applies to SONET/DWDM ring networks. When we refer to DWDM in this project, it should be understood that it also refers to WDM. SONET/DWDM ring is one of the fundamental infrastructures in most current backbone optical networks and its deployment and maintenance cost is relatively low. SONET networks consist of one or more rings that run parallelly or independently and cross-rings that form a complex mesh network (see Figure 1-1).
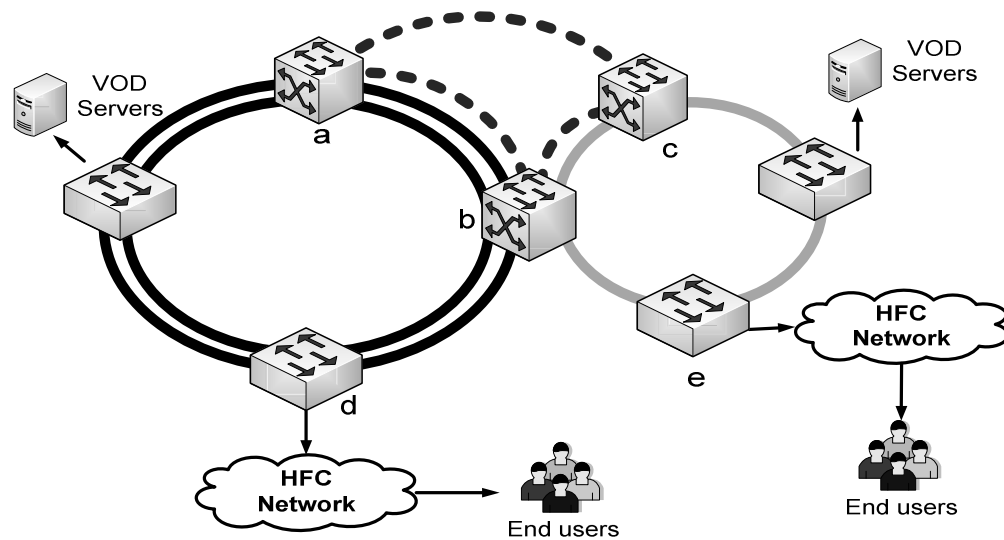
Figure 1-1: Many rings form a mesh network in a VOD network. Two dark rings run parallelly; the light colored ring can run independently or exchange data with the dark ring; the dotted ring may or may not share the routes with the other two rings. The optical signals of VOD programs in rings are converted to electronic signals and delivered to end users in Hybrid Fiber-Coax (HFC) networks.

4

Recent research [3] provides exciting revenue focused semi-protection approaches for VOD service providers who are encountering bandwidth shortage during the peak traffic time in point-to-point ring networks. These approaches take advantage of ring networks to utilize all bandwidth without having to reserve any bandwidth for full protection. In the event of a network failure in a link of the ring, the customer VOD connections to be protected are selected by their priorities and switched to the free bandwidth in the surviving link to minimize the revenue loss. The failure statistics and revenue statistics are used in [3] to assign priorities for VOD connections. The failure statistics represent the numbers of interruptions (i.e., VOD connections dropped) that customers have experienced due to limited bandwidth. We say that there is no interruption for customers if their connections are protected by the surviving link when a failure occurs in networks. The failure statistics are considered in [3] because they can be used to determine the order of priority of customers' VOD connections. Each customer may tolerate up to a certain number of interruptions. The more interruptions a customer experiences, the more likely the customer will unsubscribe from the service, which leads to lost revenue. One of the approaches suggested in [3] proposes to save the VOD connections of those customers who have experienced more interruptions than the rest to avoid losing customers. An interesting finding from [3] is that, by properly choosing connections to be protected so that the customers of these protected connections will experience no or fewer interruptions caused by failures, a network with low reliability may allow more failures without losing any customers. For example, we show a case

later in our experiments of a network that can have four failures without any revenue loss even if no customer can tolerate two interruptions caused by failures.

In Chapter 2, we survey research on cost-effective DWDM networks, focusing on the RWA and traffic grooming problems. Solving these two problems can help service providers minimize the use of some expensive components when designing and upgrading cost-effective networks. We also present a review of relevant heuristic algorithms and linear program models, which are basic tools used to design or upgrade cost-effective networks by minimizing the use of costly hardware devices or by maximizing network throughput.

In Chapter 3, we use additional statistics, the bandwidth statistics, to extend the five semi-protection approaches proposed in [3] based on assumptions and circumstances that are more realistic (e.g., more classes of customers and different bandwidth usage). The five semi-protection approaches are: Optimal, Random, Revenue, Failure, and Combination approaches. The Optimal Approach is off-line approach because to solve the optimization problem, it requires complete knowledge in advance, such as the pre-determined number of total failures, and calculates the selection of protected network traffic before all failures happen. The other approaches are on-line approaches because these approaches selectively protect/drop the network traffic at the moment that a failure happens. For the only off-line approach, Optimal Approach, we propose a new linear programming (LP) model by adding the bandwidth statistics and clarifying constraint functions for all variables. Moreover, we develop a new on-

line approach: Bandwidth Approach. Detailed algorithms to calculate the amount of VOD traffic to be dropped for different classes of customers and revenue loss rates for all the new and extended approaches are illustrated.

In Chapter 4, we conduct a 2^k factorial experimental design to analyze the effects of predictor variables and the full factorial design to analyze the performance of all the approaches. The linear programming model always yields global optimal performance (measured by revenue loss rate) based on complete knowledge in advance. In practice, Optimal Approach may not be a good choice since the number of failures cannot be pre-defined. Even though Combination Approach shows the best overall performance among the on-line approaches by locally minimizing the revenue loss, Bandwidth Approach proposed in this project outperforms the other on-line approaches in some cases. In contrast to the results in [3], by introducing the bandwidth statistics, our experimental results show that Random Approach is not the worst approach whereas Revenue Approach becomes the worst one. We compare our approaches with those in [3] and find that our approaches can achieve less revenue loss than theirs. Some performance results suggest that it is possible for service providers to achieve zero revenue loss in their networks with relatively low reliability without having to upgrade their networks and provide full protection.

We summarize the findings from this project and identify possible directions for future work in Chapter 5.

2. BACKGROUND AND RELATED WORK

In this chapter, we introduce the basic concepts involved in this project and investigate the literature on cost-effective DWDM networks, in particular, RWA and traffic grooming problems.

2.1 Concepts and Terminology

DWDM was developed from WDM optical networks, and uses more powerful and sensitive devices to space the light spectrum that is denser than that in WDM. As a result, more wavelengths that carry the data traffic can be multiplexed into a single optical fiber. DWDM has gained increasing interest in many applications [4, 5] because it can be used to accommodate the rapidly growing network bandwidth requirement, particularly in some backbone networks.

2.1.1 DWDM network foundation

To fully appreciate the importance of DWDM, it is necessary to introduce WDM because DWDM integrates the advantages of WDM, but utilizes the bandwidth of a fiber more efficiently than WDM.

Before WDM networks, traditionally network operators provided their services using some other multiplexing technologies, such as Frequency Division Multiplexing (FDM) and Time Division Multiplexing (TDM) in most of their copper cable or wireless networks.

FDM, which is a signal multiplexing scheme in non-optical networks, combines numerous different frequencies (sub-channels) on a single composite channel and sends all data streams simultaneously (see Figure 2-1). For accurate and reliable data transfer in telephony, a 4kHz frequency bandwidth including 1kHz guard-band for each analog signal (sub-channel) is suggested to prevent signals from overlapping and causing crosstalk [6] (see Figure 2-2). FDM is a copper-based or wireless scheme widely used in cable TV and radio broadcast networks.
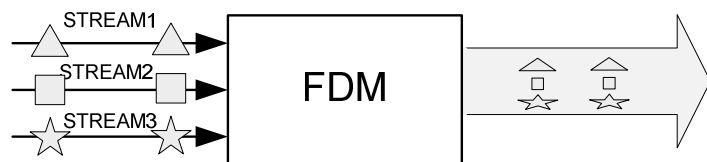
Figure 2-1: A FDM system example.
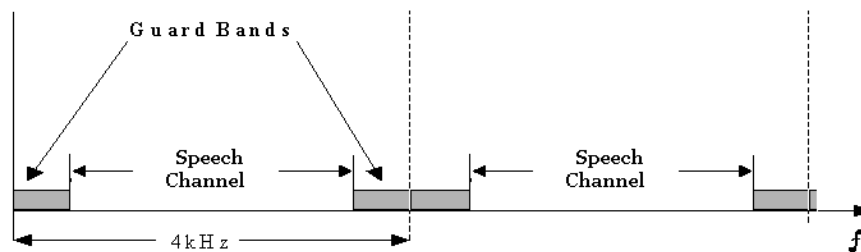
Figure 2-2: A FDM wavelength distribution.

TDM, as illustrated in Figure 2-3, multiplexes data streams that may have different transmission rates into one communication channel by assigning each stream one or more slots in a time window. Thus, TDM enables us to utilize the bandwidth of a channel more efficiently.
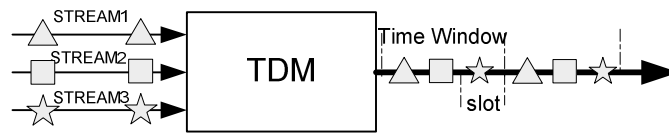
Figure 2-3: A TDM system example.

SONET (Synchronous Optical Network) and SDH (Synchronous Digital Hierarchy) are sets of standards for synchronous transmission in optical networks. SONET is the United States standard version set by American National Standards Institute (ANSI) and SDH is the international version published by the International Telecommunications Union (ITU). SONET and SDH networks have been proved successful for their high performance and cost effectiveness, and they are still under continuous development.

OC-1 (Optical Channel level 1) is the basic transmission module for SONET and STM-1 (Synchronous Transport Module level 1, equivalent to OC-3 in SONET) for SDH. OC-1 and STM-1 transmit data streams at the speed of 51.84Mbps and 155.52Mbps respectively. The transmitter hierarchy OC-N has bit rate of $N \times 51.84$Mbps by multiplexing several low speed data streams (e.g. N

OC-1 data streams) into one using TDM technology. For example, OC-48 has a speed of 2488.32Mbps (or simply, 2.5Gbps). OC-192 with a speed of 10Gbps has already been used in some networks. OC-768 with the speed of 40Gbps is still in laboratory operations.

WDM (or optical FDM) is a type of frequency division multiplexing technique that is very similar to the FDM technique. WDM combines some high frequency wavelengths (also called colors, channels, or λ) into one fiber to provide high bandwidth on the order of terabits per second (Tbps) in optical networks. To avoid confusion with FDM that also uses frequency, we use the term wavelength, instead of frequency, for WDM to represent a channel in optical networks. For example, multiplexing 10 wavelengths in a fiber where each wavelength has the speed of 10Gbps, can increase the bandwidth to 100Gbps. In the early stages of WDM networks, around year 1985, there were only two wavelengths in a fiber, which was soon increased to 16 wavelengths per fiber [7]. According to ITU-T G.694.2, a total of 18 wavelengths are defined for Coarse WDM or Conventional WDM (CWDM), whereas at least 40 wavelengths can be multiplexed in DWDM systems according to ITU-T G.694.1. Nowadays, Tbps DWDM technology, which multiplexes 128 and 160 wavelengths in one fiber by spacing a given frequency range densely, has become common [8].

SONET/DWDM ring networks combine TDM and DWDM technologies to enable network operators to utilize their bandwidth efficiently in order to accommodate the rapidly growing data traffic demand. Moreover, data in different formats, like IP, Ethernet, ATM, can transparently transport over the

11

optical layer in the DWDM network without the overhead of data encapsulation. This technology development makes it feasible for network providers to deliver diverse types of service over their networks, such as VOD service, video conferencing, telecommunication, Internet, etc.

2.1.2 Network protections on SONET/DWDM rings

Service reliability, which is considered as part of QoS, requires service providers to deploy protection architectures in their networks. Traditionally, service providers offer various types of protection. These protection schemes can be categorized into three classes: full protection, best-effort protection, and no protection. We define a new protection scheme: revenue focused semi-protection scheme.

In fully protected networks, paths with sufficient free bandwidth are set up as the backup and can be used to transmit data traffic if the primary path is interrupted. Typical fully protected architectures in SONET/DWDM rings are unidirectional path switched ring (UPSR) and bidirectional line switched ring (BLSR) [9]. In UPSR networks, one fiber works as the primary ring in the clockwise direction and the other fiber works as the protection ring with a traffic copy in the counter-clockwise direction. If a failure occurs in the path between two adjacent nodes, the nodes can switch to the protected ring to receive the data copy in the counter-clockwise direction.   In BLSR rings, all traffic is transmitted using 50% of the bandwidth of each of the two fibers that run in opposite directions. Once a failure occurs in one of the fibers, the traffic is switched to the free bandwidth in the other fiber.

Best-effort protection architectures have gained interest in some research work [10,11]. Best-effort protection networks try to protect working traffic as much as possible and/or maximize the revenue by using a mix of carefully selected protected and unprotected schemes. Sridharan and Somani [11] have used integer linear programming models to achieve the minimum cost when a failure occurs in a network. Each link has been assigned a cost value, and a currently working path disrupted by a failure will be assigned a second cost value. The solution is to find the optimal path for rerouting with the minimum cost in the event of a network failure. The survivability of a network, defined as the capability of a network to provide continuous service in case of failures is discussed in [11]. Gerstel and Ramaswami [11] reviewed different protection schemes, such as BLSR, UPSR, and Mesh Line Protection. They then studied different classes of protections from fully protected to unprotected and provided network providers with suggestions regarding choosing the right scheme depending on protection requirements and traffic types (e.g., deploying protections in either IP layers or optical layers). The authors also considered equipment cost and bandwidth efficiency as two important factors in a cost-effective design.

Similar to best-effort protection schemes, our revenue focused semi-protection scheme uses less bandwidth as backup than full protection schemes but it requires no reserved bandwidth, traffic routes, or pre-defined levels of protection. When failures occur in networks, traffic is selectively protected by any

free bandwidth in the other links to minimize the revenue loss caused by network failures.

2.1.3 Cost-effective problems in SONET/DWDM rings

With DWDM technology, SONET networks can support large bandwidth on a single fiber. However, the more wavelengths used, the more optical and electronic multiplexing equipment required, which dominates the cost of SONET/DWDM ring networks. Three costly components commonly used in a SONET/DWDM ring network are shown in Figure 2-4: wavelength converters, OADMs, and SADMs.
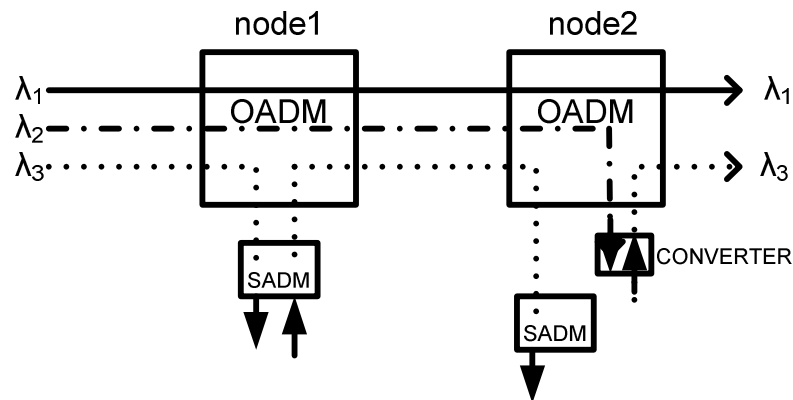
Figure 2-4 : Cost-dominant components in SONET/DWDM rings.

Converter: A converter receives a wavelength (λ_2 in Figure 2-4) and re-transmits the data using a different wavelength (λ_3 in Figure 2-4). A converter may be used when data traffic arrives on a wavelength that has already been used in the fiber through which the converter sends data. Several studies [12,13] have shown that using optical converters may reduce wavelength usage in some

cases, but it is still costly compared to the number of the wavelengths saved. To simplify research problems in this project, we consider a point-to-point communication request between two nodes and data transmitted along a lightpath. A lightpath is an all-optical transmission path that is assigned a wavelength, and there is no wavelength conversion or optical-electronic-optical processing at intermediate nodes.

OADM: Optical Add/Drop Multiplexers offer the ability to selectively add/drop a wavelength that carries only the data destined to or originating from a node. Incoming wavelengths that do not contain data for the node will bypass the OADM (λ_1 and λ_2 bypass node 1 in Figure 2-4). There must be at least one OADM at a node if there is traffic destined to or originating from this node.

SADM: SONET Add/Drop Multiplexers extract the low bit-rate streams from a multiplexed wavelength and/or add a data stream in the same wavelength for its destination node (see Figure 2-4). For example, a SADM drops an OC-3 data stream from a wavelength with an OC-12 integrated data stream, and adds its own OC-3 data stream into the same wavelength and retransmits to its destination. Therefore, a SADM is needed at a node only when a wavelength channel carries incoming or outgoing low bit-rate streams for this node.
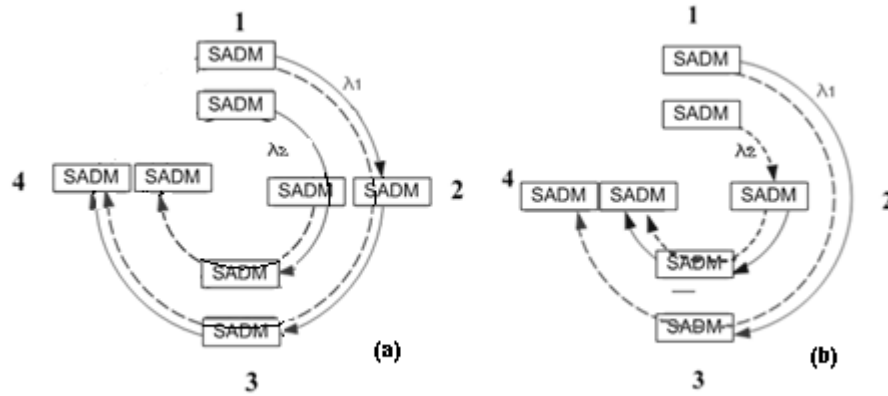
Figure 2-5: SADM usage in SONET/WDM with 4 nodes and 2 wavelengths.

Figure 2-5 (a) shows a unidirectional ring example without considering minimizing the usage of SADMs. Suppose that the unidirectional communication request set is {(1,2), (1,3), (1,4), (2,3), (2,4), (3,4)}, there are two given wavelengths: $\lambda 1$ and $\lambda 2$, and each wavelength can aggregate two OC-3 data streams denoted by solid and dotted lines. To realize all the requests without concern for the SADM usage, a total of eight SADMs are used in Figure 2-5 (a) (one OADM for each node is not shown in the figures). By properly using the wavelength routing and assignment scheme, we can reduce the number of SADMs to seven by bypassing node 2 for the wavelength $\lambda 1$, as shown in Figure 2-5 (b).

This example illustrates two of the optimization problems examined in current research: routing and wavelength assignment (RWA) and traffic grooming.

The **RWA** problem [14] is to find lightpaths for given connection requests and to assign wavelengths to the lightpaths to meet the distinct wavelength constraint and wavelength continuity constraint. The distinct wavelength constraint requires that all lightpaths transmitted in the same fiber must be assigned distinct wavelengths. The wavelength continuity constraint requires that there be no wavelength conversion and electronic processing at intermediate nodes. The objective of RWA is to realize all communication requests using a minimum number of wavelengths or to maximize the traffic throughput using a given number of wavelengths. If the routes for all requests are given in advance, RWA problems can be reduced to WA (wavelength assignment) problems.

Traffic grooming in DWDM networks is a process to realize the given traffic requests and minimize the use of SADMs by selectively grouping low data-rate streams into a high data-rate output. A grooming factor refers to the number of low data-rate streams that are multiplexed into one wavelength. For example, in SONET/DWDM networks, an OC-48 SADM multiplexes four OC-12 low-rate traffic streams into an OC-48 wavelength channel, and in this case, the grooming factor is 4. As ADMs dominate the cost of DWDM networks, it is very important to solve the traffic grooming problem in order to design cost-effective networks.

2.2 Related Work

To solve the RWA and traffic grooming problems, it is necessary to optimize the use of wavelengths and SADMs. These problems have been proved NP-hard [15,16,17] in mesh and ring networks. Thus, heuristic algorithms should be applied to achieve the best possible performance. A lot of research has been

conducted on different network topologies, such as rings [16,27,33,34], mesh networks [18,19,20,21], and trees [22,23,24] with or without considering wavelength conversion. Some previous work [25] on coloring problems in graph theory is also considered to provide solutions to RWA problems. Our review focuses on the research for DWDM networks without wavelength conversion.

2.2.1 Routing and wavelength assignment

Ramaswami and Sivarajan [18] address the RWA optimization problem using an integer linear program (ILP) model to maximize the number of connections that are successfully routed for an arbitrary mesh network with a given limited number of wavelengths. In addition, they derive an upper bound on the number of connection requirements in their linear program (LP) model, by relaxing the integrality constraints in ILP. An LP model in [12] considers RWA in ring networks without wavelength conversion. The objective of the RWA LP model is to minimize the number of required wavelengths. Variables are introduced in these models to indicate whether a certain path is selected for one connection and assigned one of the given wavelengths. The constraint functions in these models include a constraint with a given number of wavelengths, and distinct wavelength and wavelength continuity constraints.

More research on static traffic requests can be found in [26,27], which proposed several heuristic algorithms to identify the proper lightpaths to be assigned wavelengths so that the number of wavelengths is minimized. Some greedy heuristic algorithms are presented and evaluated in [26] for both static and dynamic traffic patterns with bounded and unbounded numbers of

18

wavelengths. The heuristic algorithms suggested in [26, 27] assign a given wavelength to each lightpath from the longest one to the shortest one in order to maximize the use of each wavelength. In [27], the authors give a lower bound on the number of wavelengths required, $W = \left\lceil \frac{N^2-1}{8} \right\rceil$ where N is the total number of nodes, to realize all connection requests between all pairs of nodes in a DWDM ring with two working fibers and two protection fibers.

The authors in [28] further proved that for a fully connected ring network, which is a network having connections between all pairs of nodes, the lower bound on the number of wavelengths required is $W = \left\lceil \frac{N^2}{8} \right\rceil$ if N is even, and $W = \left\lceil \frac{N^2-1}{8} \right\rceil$ if N is odd.

A RWA algorithm for connection maximization in undirected DWDM ring networks with an approximation ratio 2/3 is presented in [29] and is considered to be an improvement of $(1 - \frac{1}{e})$-approximation in [30] (where e is the base of the natural logarithm function). A $\frac{7}{11}$-approximation algorithm is also given in [29] by using the Chain-and-Matching technique for directed rings.

2.2.2 Traffic grooming

To solve the traffic grooming problem is to minimize the use of SADMs in networks by multiplexing low-rate data streams into one high-rate wavelength channel. In [31], the authors show that minimal number of wavelengths and minimal number of SADMs are two objectives that cannot be achieved simultaneously in their cases. It has been suggested that the traffic grooming

problem is more important than RWA when designing cost-effective DWDM networks. For example, the researchers in [32,33] argue that the first-order optimization goal should be to minimize the use of SADMs rather than to save the number of wavelengths unless the wavelength limit is exceeded.

In [33], the authors derive a lower bound on the number of SADMs used and an upper bound on the performance of two greedy heuristics, which are Cut-First and Assign-First. The lower bound is described as

$$\alpha \geq \alpha_{lowerbound} = \Sigma_k(\sigma_k + \tau_k - \min\{\sigma_k, \tau_k\}) \text{ ,}$$

where σ_k is the total number of lightpaths departing from node k and τ_k is the total number of lightpaths ended at node k. The lower bound is derived based on the ideas that each pair of source and destination nodes requires one SADM and the shared SADMs are bounded by $\min\{\sigma_k, \tau_k\}$.

In [34], the authors achieve the same lower bound for the number of SADMs, but argue that the performance analysis of the Assign-First algorithm in [33] is incorrect and demonstrated so by giving a counter-example. Furthermore, the authors propose another three greedy heuristics: Iterative Merging, Iterative Matching, and Euler Cycle Decomposition.

Similar to research on RWA problems, some ILP models have been proposed [35,36,37] for addressing traffic grooming problems.

For an arbitrary graph in UPSR rings with symmetric traffic patterns, solutions to the k-Edge-Partitioning problem are used in [38,39,40,41] to solve traffic grooming problems by partitioning a traffic graph G into subgraphs with at

most k edges. The basic idea common to all four papers is to minimize the number of nodes, which may possibly decrease the number of connected components in each subgraph, thereby decreasing the number of ADMs used. Wang and Gu in [41] derive a better algorithm using an *r*-regular graph (all nodes in a graph has the same degree *r*) and summarize the performance results of all the relevant algorithms in one table (Table 1).

	Required SADMs for even r	Required SADMs for odd r	Required wavelengths
Algorithm in [38]	$\left\lceil \lvert E(G)\rvert(1+\frac{1}{k}) \right\rceil$	$\left\lceil \lvert E(G)\rvert(1+\frac{1}{k}) \right\rceil + \frac{n}{2}$	$\left\lceil \frac{E(G)}{k} \right\rceil$
Algorithm in [39]	$\left\lceil \lvert E(G)\rvert(1+\frac{2}{k}) \right\rceil$	$\left\lceil \lvert E(G)\rvert(1+\frac{2}{k}) \right\rceil$	$\left\lceil \frac{E(G)}{k} \right\rceil$
Algorithm in [40]	$\left\lceil \lvert E(G)\rvert(1+\frac{1}{k}) \right\rceil + \left\lfloor \frac{n}{4} \right\rfloor$	$\left\lceil \lvert E(G)\rvert(1+\frac{1}{k}) \right\rceil + \left\lfloor \frac{n}{4} \right\rfloor$	$\left\lceil \frac{E(G)}{k} \right\rceil$
Algorithm in [41]	$\left\lceil \lvert E(G)\rvert(1+\frac{1}{k}) \right\rceil$	$\left\lceil \lvert E(G)\rvert(1+\frac{1}{k}) \right\rceil + (\frac{3n}{2(r+1)} - 1)$	$\left\lceil \frac{E(G)}{k} \right\rceil$

Table 1: Performance result comparison between algorithms [41].
k is the grooming factor and n is the number of nodes.

3. REVENUE FOCUSED SEMI-PROTECTION MODELS

In this chapter, we develop revenue focused semi-protection models to design cost-effective networks. Our goal is to minimize the revenue loss when providing VOD service in a DWDM ring network by overcoming bandwidth shortages without incurring any hardware upgrade costs.

3.1 Semi-protected Application Scenarios

Traditional DWDM ring networks use either non-protection or full protection schemes. With the fast growth of video content transmission services, many service providers face the problem of bandwidth shortage in their ring networks. Common strategies that service providers have adopted to handle the challenge of bandwidth shortage while minimizing the network updating cost or revenue loss include: i) using new techniques to increase their bandwidth, such as optical hardware upgrades in DWDM networks; ii) setting up additional optical fibers to accommodate more network traffic; iii) giving up backup routes for full protection and using all bandwidth as primary traffic deliverer; and iv) making no new investment in existing networks and disconnecting traffic randomly at the cost of possible revenue loss when failures occur in peak traffic time. None of the above strategies is optimal: all the strategies will increase either cost or revenue loss. Not much research has been done to improve these strategies using customer statistics.

In this chapter, we develop revenue focused semi-protection approaches to minimize the revenue loss by using customer statistics to determine the priorities of all VOD connections. The solution achieved in this project provides service providers with guidelines on the design or upgrade of cost-effective networks. In practice, service providers have access to customer statistics from customer surveys and online tracking records that suggest when a customer is ordering or watching a VOD program. We believe that introducing the new bandwidth statistic will not cost much more than only using the other two statistics in [3].

Revenue statistics: Revenue statistics refer to subscription fees paid by customers. We categorize customers into three classes: high-revenue, moderate-revenue, and low-revenue customers.

Failure statistics: A customer experiences a network interruption when a failure happens in a network and the VOD connection of the customer is chosen to be dropped. The Failure statistic is the number of VOD service interruptions that a customer experiences during a period of operation. Assuming that customers can tolerate up to a certain number of network interruptions before they unsubscribe from VOD programs, the more interruptions a customer experiences, the more likely the customer will unsubscribe. Statistics can be used to indicate customers' tolerance of network interruptions; these statistics are proportional to customers' expectations of network reliability. It is reasonable to assume that customers who pay higher subscription fees (i.e., higher revenue customers) hold higher expectations. Therefore, experiencing the same number

of interruptions, higher revenue customers are more likely to unsubscribe than lower revenue customers. In our project, to examine the effect of the number of interruptions on revenue loss, we focus on revenue loss caused by customer unsubscription from VOD service only after experiencing network interruptions.

Bandwidth statistics: Bandwidth statistics are the average bandwidths of VOD programs required for different classes of customers. The authors [3] have examined two different classes of customers (high- and low-revenue customers) who have the same bandwidth usage. We assume that three different classes of customers watch three different types of VOD programs: SD (Standard Definition) VOD for low-revenue customers, DVD- quality VOD for moderate-revenue customers, and HD (High Definition) VOD programs for high-revenue customers. On average, SD, DVD-quality, and HD VOD programs occupy 3.75Mbps, 9.8Mbps, and 19Mbps bandwidths [42] respectively.

Some other impact factors (which are predictor variables in our experimental designs) are evaluated, such as the probabilities customers are watching when a failure happens, the composition ratio of the three classes of customers, and the ranking impact factor for assigning the priorities to all customers.

3.2 A Semi-protection Scheme

Similar to [3], we develop a semi-protection scheme for simple point-to-point DWDM ring networks (Figure 3-1). In such a DWDM ring network, the server node provides VOD service to a customer distribution node through the

two point-to-point links between the two nodes, and there is no specific backup

route reserved to protect the network when failures occur. Our scheme applies to

the situation when a failure occurs during the peak traffic time (e.g. the optical

fiber is broken) and the surviving link cannot accommodate the entire traffic load.

Consequently, some VOD connections have to be dropped, and some

connections are protected by the free bandwidth in the surviving link. To handle

this challenging situation, Gerstel et al. [3] proposed two semi-protection

schemes: non-preemptive protection and victimized protection.
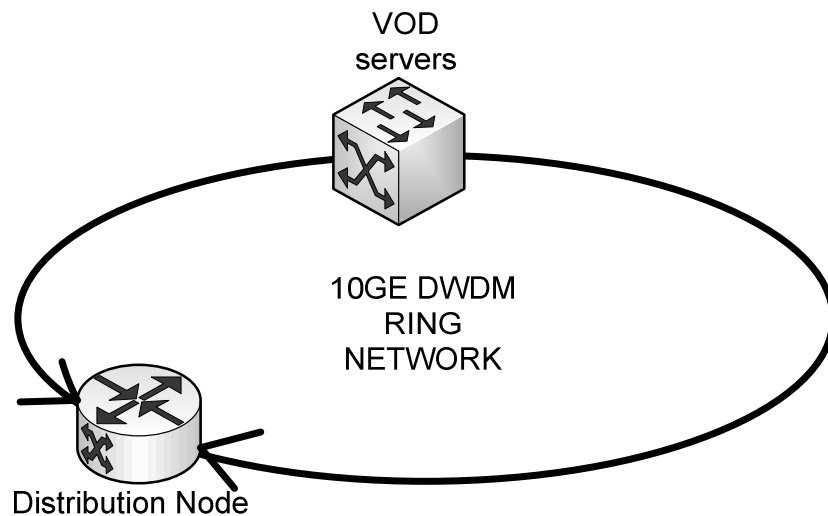
Figure 3-1: A point-to-point DWDM ring network

In non-preemptive protection, when a failure happens in one of the two

links, a selection of connections in the broken link is saved by using the free

bandwidth in the surviving link. All the original traffic in the surviving link is

uninterrupted. In victimized protection, some VOD connections in the surviving

link are assigned lower priorities than selected connections from the broken link

and thus become victims to be dropped in order to free bandwidth for those higher priority connections. Our project focuses on the victimized protection scheme because the victimized protection scheme yields better performance than the non-preemptive protection scheme in terms of minimizing revenue loss. The victimized protection scheme selects connections to be protected based on priorities assigned to all the connections in both surviving and broken links, whereas the non-preemptive protection scheme selects based on the priorities assigned to all the connections in the broken link only.

3.2.1 Notation

We use the following notation in our models and experiments.

c: Class c customers, where $c \in \{0, 1, 2\}$ represents low-revenue, moderate-revenue and high-revenue customers respectively in our simulation.

f: The number of interruptions a customer has experienced.

F: The total number of failures occurring in the operation period.

$r(c)$: The revenue rate generated by a class c customer.

revenue-ratio: The revenue generation ratio between the revenue rates of the three classes of customers, denoted $r(0){:}r(1){:}r(2)$.

$b(c)$: The bandwidth required for each class c customer.

T_t: $t \in \{0, 1, ..., F + 1\}$, The time right before the tth failure happens in the operation period $[T_0, T_{F+1}]$, where T_0 represents the initial time in the operation period before any failure happens.

(c, f, t)-*customers*: The group of class c customers at time T_t who have experienced f interruptions. We also use (c)-*customers* to mean class c customer and (c, f)-*customers* to refer to the class c customers who have experienced f interruptions.

$N(c, f, t)$: The number of (c, f, t)-*customers*.

$n(c, f, t)$: The traffic load caused by the (c, f, t)-*customers* when they are watching VOD programs.

$O(c)$: The number of new (c)-*customers* joining the VOD service during the period between two adjacent failures.

$o(c)$: The traffic load caused by the new (c)-*customers* when they are watching VOD programs.

$D(c, f, t)$: The number of dropped (c, f, t)-*customers* when the tth failure happens.

$d(c, f, t)$: The amount of dropped traffic load of (c, f, t)-*customers* when the tth failure happens.

triple-ratio: The ratio of the number of initial (c)-*customers* in the network at $T_t = 0$, denoted $N(0,0,0) : N(1,0,0) : N(2,0,0) = x : y : z$. We also

27

assume that new customers subscribing to the service satisfy the same ratio.

ratio(c): The initial ratio of the number of (c)-*customers* to the number of $(c + 1)$ -*customers*, If $N(0,0,0){:}N(1,0,0){:}N(2,0,0) = x{:}y{:}z$, then, $ratio(0) = x/y$, and $ratio(1) = y/z$. The new customers subscribing to the service satisfy the same ratio.

$pw(c)$: The probability of a (c)-*customer* watching a VOD program at the peak traffic time.

$pun(c,f)$: The probability of a (c,f) -*customer* unsubscribing from the service if the customer is dropped at the next failure.

$w(c,f)$: The priority value that is assigned to a (c,f) -*customer* in Combination Approach.

L: The capacity of one point-to-point link in the ring.

3.2.2 Model assumptions and statement

Our models do not apply to failures during non-peak traffic time. We assume that there is no revenue loss during non-peak traffic time because all the traffic can be saved by the free bandwidth in the surviving link and no customers will experience interruptions. To simulate cases in peak traffic time, we develop our models by adopting some similar assumptions to those described in [3]:

1. Initially, there is a certain number of (c) -*customers* at time T_0 , satisfying the *triple-ratio*, which is the ratio among the numbers of

28

customers in each class. All the initial traffic is evenly distributed between the two point-to-point links between the VOD server node and customer distribution node in the ring. The total amount of the initial traffic is equal to the bandwidth capacity of a link, thus half of the bandwidth in each link is occupied by the initial traffic;

2. When a failure happens, some connections are dropped and there may be customers who unsubscribe from the network. To ensure that the total traffic always exceeds the bandwidth in the surviving link, there are some new customers joining the network in the intervals between adjacent pairs of failures, including the intervals of $[T_0, T_1]$ and $[T_F, T_{F+1}]$. The number of new customers distributed across the three different classes also satisfies the *triple-ratio*;

3. If no failure happens during the operation period $[T_0, T_{F+1}]$, the total amount of initial traffic and the traffic caused by the new customers should be equal to the full capacity of the two links at the end time T_{F+1};

4. All the traffic caused by all the new customers during the operation period, which is equal to the capacity of one link, is evenly distributed in the intervals between adjacent pairs of failures. Based on the *triple-ratio*, the bandwidth consumption of each class of customers, and the number of failures F during the operation period, the constant number of new customers joining in each failure interval during one operating period then can be determined. Despite our assumption, we

acknowledge that in reality, the number of new customers added to each interval between two adjacent failures may not be constant because the failures are not evenly distributed in real time. To get a sense about how randomly occurring failures may affect revenue loss, we also study a case that simulates three situations when varying numbers of new customers join in the service in each interval between two adjacent failures.

At time T_0, we use $N(c,0,0)$ to denote the initial number of (c)-customers who have never experienced any failures. T_t is the time right before the tth failure, where $t = 1,2 ..., F$. Therefore, during the time $[T_0, T_{F+1}]$, there are in total F failures. At any time T_t, each (c)-*customer* is watching VOD programs with probability $pw(c)$. The initial traffic load, denoted $n(c,0,0)$, is equal to the fixed capacity L of one link. There is always a constant number of new customers, $O(c)$, joining the network and contributing the traffic load $o(c)$ during the time interval between adjacent failures. In order to ensure that the total number of customers at any time exceeds the capacity of one link, but is not greater than the total capacity of the two links at the end time T_{F+1}, the total initial traffic $\sum_{c=0}^{2} n(c,0,0) = L$ is evenly distributed in the two links, thus $L/2$ for each link. The constant amount of traffic load $\sum_{c=0}^{2} o(c) = \frac{L}{F+1}$ generated by the new customers $O(c)$, is determined by the total number of failures in an experimental period and will keep increasing the total traffic to $2L$ at the end time T_{F+1} if no customers leave. The number of initial (c)-*customers* and all the new customers

added across the three different classes satisfy the $triple-ratio,$ and $\frac{N(c,0,0)}{N(c+1,0,0)} =$

$\frac{O(c)}{O(c+1)} = ratio(c), c = \{0,1\}.$ The probability of a (c,f,t)-*customer* unsubscribing

from the network is $pun(c,f)$ after they experience $f+1$ interruptions. The

revenue loss rate then can be calculated with the revenue loss caused by all the

leaving customers divided by the total revenue when no customer leaves.

3.3 Off-line Approach: Optimal Approach

To achieve an optimal cost-effective semi-protection scheme, we extend

the linear programming model, which was developed in [3]. Our goal is to

minimize the total revenue loss rate at the end time T_{F+1} by calculating the

optimal amount of dropped connections carefully selected using the customer

statistics. Therefore, $n(c,f,t)$ and $d(c,f,t)$ are the variables that need to be

determined in the model.

Suppose a (c)-*customer* is watching a VOD program with probability

$pw(c)$, and each customer who is watching the program is occupying

bandwidth $b(c)$. Then we have the following equation to describe the relation

between the number of (c,f,t)-*customers* and the amount of traffic caused by

these (c,f,t)-customers at any time T_t.

$$n(c,f,t) = N(c,f,t) \times b(c) \times pw(c) \qquad\qquad ---- (1),$$

$$where\ c = 0,1,2,\ f = 0,1,...,F,\ t = 0,1,...,F+1,\ f \le t\ ^{*1}.$$

---

*1 No any customer experiences more than $t-1$ failures at time $T_t,$ which is the time just before
the tth failure happens, so $f \le t$ throughout our project.

At time T_0, none of the initial customers experience interruptions, and the total amount of their traffic is set to equal the capacity L. The new customers joining the network are evenly distributed in all failure intervals and the total traffic caused by all new customers at end time T_{F+1} is equal to the capacity L:

$$\sum_{c=0}^{2} n(c,f,t) = L, \quad where\ t = 0, f = 0 \qquad ---(2),$$

$$\sum_{c=0}^{2} o(c) = \frac{L}{F+1}, \quad in\ each\ failure\ interval \qquad ---(3).$$

And the ratios of the numbers of initial (c)-*customers* satisfy the *ratio(c)*:

$$\frac{N(0,f,t)}{N(1,f,t)} = ratio(0), \quad where\ t = 0, f = 0 \qquad ---\ (4),$$

$$\frac{N(1,f,t)}{N(2,f,t)} = ratio(1), \quad where\ t = 0, f = 0 \qquad ---(5).$$

So do the number of newly joined customers across different classes of customers, for each failure interval:

$$\frac{O(0)}{O(1)} = ratio(0) \qquad ---(6),$$

$$\frac{O(1)}{O(2)} = ratio(1) \qquad ---(7).$$

The linear equations (1)--(7) calculate the initial number of customers at time T_0, the number of new customers at each time interval T_t, and the amount of traffic generated by all these customers.

Then we have the following equations for the number of $(c, f, t + 1)$ - *customers*, and the number of selectively dropped customers at time T_t.

$$N(c, f, t + 1) = N(c, f, t) - D(c, f, t) + O(c), where\ f = 0 --- (8).$$

Equation (8) shows that the number of customers who have not experienced any failures by time T_{t+1} equals the number of $(c, 0, t)$-*customers* that were not dropped at time T_t plus the number of newly joined customers during time $[T_t, T_{t+1}]$.

Equation (9) describes that $(c, f, t + 1)$-*customers* (where $f > 0$) consist of: *1)* customers who had experienced f interruptions and were not dropped at time T_t and *2)* customers who had experienced $f - 1$ interruptions and were dropped at time T_t but will keep subscribing to the VOD service.

$$N(c, f, t + 1) = N(c, f, t) - D(c, f, t) + \left(1 - pun(c, f - 1)\right) \times D(c, f - 1, t),$$

$$where\ f > 0 \qquad\qquad --- (9).$$

Using equations (8) and (9), we get the following equations describing traffic load:

$$n(c, f, t + 1) = n(c, f, t) - pw(c) \times d(c, f, t) + o(c), where\ f = 0 --- (8)',$$

and

$$n(c, f, t + 1) = n(c, f, t) - pw(c) \times d(c, f, t) +$$

$$pw(c) \times \left(1 - pun(c, f - 1)\right) \times d(c, f - 1, t),$$

$$where\ f > 0 \qquad\qquad --- (9)'.$$

The next step is to determine the amount of traffic caused by each group of (c, f, t)-*customers* that we have to disconnect when the tth failure happens. We assume that the fixed capacity of each link is L, and then the dropped traffic that exceeds the capacity of one link caused by the tth failure can be calculated by:

$$\sum_{c=0}^{2} \sum_{f=0}^{t-1} d(c,f,t) = \max \left\{ 0, \sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c,f,t) - L \right\}.$$

Since we only model the situation during the peak traffic time when there is not sufficient capacity in the surviving link for all VOD connections, some of the connections have to be dropped if a failure occurs. Therefore, the above formula can be simplified:

$$\sum_{c=0}^{2} \sum_{f=0}^{t-1} d(c,f,t) = \sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c,f,t) - L \qquad --- (10).$$

So far, we have explained all the linear equations for the linear programming model. Additional constraints for this model are introduced in (11)-(12).

$$d(c,f,t) \leq n(c,f,t) \qquad --- (11).$$

The constraint (11) shows that at the time when the tth failure happens, the amount of the dropped traffic cannot exceed the current traffic of $n(c,f,t)$. Moreover, all the variables in the model are non-negative numbers, so we have

$$d(c,f,t) \geq 0 \qquad --- (12),$$

and

$$n(c,f,t) = 0, \; when \; f = t \qquad --- (13).$$

It is true that $n(c,f,t) \geq 0$ when $f \leq t$ from (11) and (12). As we have mentioned before, it is not possible that $f > t$. When $f = t$, the constraint (13) must be specified either in the data initialization part or added as a constraint function in the model. This is because we need the value of $n(c,f,t)$ to calculate the traffic of $n(c,f,t+1)$ in equations (8)' and (9)'. If $f = t$ and $n(c,f,t)$ is not specified to be 0, the linear program model will consider $n(c,f,t)$ to be a variable and may assign it any non-zero value to optimize its performance. As a result, the dropped traffic $d(c,f,t)$, when $f = t$, can also be assigned a non-zero value. This is not what we expect because at time T_t, just the moment before the tth failure happens, no customer has experienced t failures. For example, according to equation (9)', the amount of traffic by $(c,2,3)$-$customers$ at time T_3 can be calculated by $n(c,2,3) = n(c,2,2) - pw(c) \times d(c,2,2) + pw(c) \times (1 - pun(c,1)) \times d(c,1,2)$, and $n(c,2,2)$ and $d(c,2,2)$ should always be zero because no customers have experienced two interruptions at time T_2.

Finally, we introduce our objective function, maximizing the sum of total revenue generated by all customers at time T_{F+1}.

$$\text{Maximize} \sum_{c=0}^{2} \sum_{f=0}^{F} r(c) \times N(c,f,F+1) \quad --- (14)$$

Alternatively, using the total traffic left at time T_{F+1}, we can formulate the objective function as

$$\text{Maximize} \sum_{c=0}^{2} \sum_{f=0}^{F} \frac{r(c) \times n(c,f,F+1)}{b(c) \times pw(c)} \quad --- (14)'.$$

35

We measure and compare the performance of our model with that of other approaches using the revenue loss rate. Therefore, we transform $(14)'$ to (15).

$$\text{Minimize } (1 - \sum_{c=0}^{2} \sum_{f=0}^{F} \frac{r(c) \times n(c,f,F+1)}{b(c) \times pw(c)} / \sum_{c=0}^{2} \frac{2 \times r(c) \times n(c,0,0)}{b(c) \times pw(c)}) \ - - - (15),$$

The part $\sum_{c=0}^{2} \frac{2 \times r(c) \times n(c,0,0)}{b(c) \times pw(c)}$ in (15) is the total revenue generated by all customers at end time T_{F+1} if no customer unsubscribes during the operation period. This total revenue is the initial revenue at time T_0 times 2 because the total amount of the newly added traffic equals the amount of the initial traffic.

The solution of this linear program is the best among all our revenue focused semi-protection approaches. However, it should be noted that this model is an off-line approach because the number of failures cannot be predicted in advance in reality. The global optimal solution may not be optimal for each time T_t where $t < F + 1$, which we will illustrate in our specific case studies.

3.4 On-line Approaches

All the on-line approaches proposed in this project determine which VOD connections to save in the event a failure by assigning priorities to different groups of customers. Different from the LP model that determines connections to be dropped at the beginning of each experimental period based on a predefined number of failures, all the on-line approaches calculate the amount of traffic to be dropped each time when a failure occurs, case by case. Detailed algorithms for comparing the performance of all the on-line approaches are examined in the following sections.

3.4.1 Random Approach

In Random Approach, all customers are assumed to be of the same priority. We randomly select the VOD connections (for example, by randomly selecting customer IDs from the customer database) to be dropped among (c, f, t)-*customers* when a failure occurs. Because no specific statistics are used to assign priorities to customers, the algorithm to randomly select the protected customers is similar to [3].

The amount of dropped traffic for (c, f, t)-*customers* is calculated using the following equation:

$$d(c, f, t) = \left(\frac{n(c,f,t)}{\sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c,f,t)} \right) \left(\sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c, f, t) - L \right),$$

where $\sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c, f, t) - L$ is the total amount of dropped traffic that exceeds the capacity, and $\left(\frac{n(c,f,t)}{\sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c,f,t)} \right)$ is the proportion of the traffic for each group of (c, f)-*customers* to the total amount of traffic at time T_t. To simulate the algorithm in [3] and examine the performance of our extended approach, we use our algorithm to calculate revenue loss rates shown in Figure 3-2.

1) data initialization;
2) for (t=1; $t <= F$+1; t++)
3)   calculate the traffic $n(c, f, t)$ at time T_t, for each c and f;
4)   calculate $sum(t) = \sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c, f, t)$ at time T_t;
5)   if $t < F$+1
6) $dropped\_traffic(t) = sum(t) - capacity$;
7) $d(c, f, t) = dropped\_traffic(t) * \frac{n(c,f,t)}{sum(t)}$, for each c and f;
8) Output

   $revenue\ loss\ rate =$

   $(\sum_{t=0}^{F} \sum_{c=0}^{2} \sum_{f=0}^{F} \frac{r(c) \times d(c,f,t) \times pun(c,f)}{b(c)}) / \text{revenue\_noleaving}$;

**Figure 3-2: Algorithm to calculate revenue loss rate
for Random Approach**

In step 1, all data is initialized, including the initial traffic at time T_0 and newly joined traffic during each interval. Step 3 calculates the current traffic for each group of (c, f, t)-*customers* at time T_t using the same functions (8)' and (9)' as in the linear programming model. The total traffic $sum(t)$ is summed up at step 4 and is used to calculate the proportion of the traffic for (c, f)-*customers* to be dropped at step 7. We only consider the case $t < F + 1$ at step 5 because the last failure, that is, the Fth failure, happens right after time T_F and there is no traffic dropping at the end time T_{F+1}. Step 8 specifies that the revenue loss rate, which expresses our later experimental results, is the ratio of the actual total revenue loss caused by all the customers who unsubscribed from the VOD service to the expected total revenue assuming there is no unsubscription during the experimental period.

3.4.2 Revenue Approach

Revenue Approach is the first approach for which we use revenue statistics to minimize revenue loss. The basic idea of Revenue Approach is to select the VOD connections to be dropped by assigning a priority to each customer based on revenue statistics and then drop customers, in order of assigned priority (starting from the lowest priority). Once the number of dropped connections for (c)-*customers* is determined at time T_t, Random Approach is used to choose customers to be dropped according to the proportion of the number of (c, f, t)-*customers* to the number of (c)-*customers* when the tth failure happens. We describe in more detail the algorithm in [3] to calculate the amount of protected/dropped VOD traffic and revenue loss rates for Revenue Approach in Figure 3-3.

In Revenue Approach, at each time T_t, $sum(c)$ is calculated for all the traffic caused by (c)-customers in step 5. From step 9, the traffic to be dropped at each time T_t is calculated for (c)-*customers,* starting from low-revenue up to moderate- and high-revenue customers. If the traffic to be dropped is greater than the number of (c)-*customers,* all the (c)-*customers* will be dropped as shown in step 12. Otherwise, the connections to be dropped are determined using Random Approach according to the ratio of the traffic to be dropped for (c, f)-*customers* to the total amount of dropped traffic, as shown in step 16.

1) data initialization;
2) for (t = 1; t <= F+1; t++)
3)   calculate the traffic $n(c, f, t)$ at time T_t for each c and f;
4)   calculate $sum(t) = \sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c, f, t)$ at time T_t;
5)   calculate $sum(c) = \sum_{f=0}^{t-1} n(c, f, t)$ at time T_t for each c;
6)   if t < F+1   // no drop for T_{F+1};
7) $dropped\_traffic(t) = sum(t) - capacity$;
8)   temp = $dropped\_traffic(t)$;
9)   for (c = 0; c <= 2; c++)
10)   if $sum(c) \leq temp$
11)   for (f = 0; f < t; f++)
12) $d(c, f, t) = n(c, f, t)$;
13) $temp = temp - n(c, f, t)$;
14)   else if $sum(c) > temp$
15)   for (f = 0; f < t; f++)
16) $d(c, f, t) = temp * \frac{n(c,f,t)}{sum(c)}$;
17) $temp = 0$;
18) Output

$revenue\ loss\ rate =$

$(\sum_{t=0}^{F} \sum_{c=0}^{2} \sum_{f=0}^{F} \frac{r(c) \times d(c,f,t) \times pun(c,f)}{b(c)}) / revenue\_noleaving$

**Figure 3-3: Algorithm to calculate revenue loss rate
for Revenue Approach**

3.4.3 Bandwidth Approach

After introducing the bandwidth statistic, Bandwidth Approach is used to maximize VOD connections to be saved by dropping connections that use more bandwidth first. As mentioned earlier, one of our assumptions in this project is that higher revenue customers use more bandwidth. Therefore, the priority values assigned to VOD connections in Bandwidth Approach are ranked in the

reverse order to those in Revenue Approach. The algorithm for Bandwidth Approach is similar to the algorithm for Revenue Approach, which is shown in Figure 3-3, except that we reverse the iteration in step 9 and run it from high revenue to low to choose VOD connections to be dropped when a failure occurs.

3.4.4 Failure approach

Failure Approach determines VOD connections to be dropped using failure statistics. Failure statistics record the numbers of interruptions that customers have already experienced and can give us a sense about the likelihood that customers unsubscribe from network service after experiencing a certain number of interruptions. The more interruptions a customer experiences, the more likely the customer will unsubscribe from the VOD service, which, in turn, leads to revenue loss. Therefore, in Failure Approach, customers who have experienced more interruptions are assigned higher priorities and their connections will be saved. Within a group of (c, f, t)-*customers* who have the same priority, the connections to be dropped are determined using Random Approach. The algorithm to examine the performance for Failure Approach is shown in Figure 3-4. In step 5, instead of calculating the total traffic of (c)-customers as in Revenue Approach, we calculate the total traffic of each group of customers (customers who have experienced the same number of interruptions *f* are categorized into one group). Step 9 through 17 iteratively calculate the amount of traffic to be dropped for each group of *(c, f, t)-customers* at each time T_t.

1) data initialization;
2) for ($t = 1$; $t <= F+1$; t++)
3)   calculate the traffic $n(c, f, t)$ at time t for each c and f;
4)   calculate $sum(t) = \sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c, f, t)$ at time T_t;
5)   calculate $sum(f) = \sum_{c=0}^{2} n(c, f, t)$ at time T_t, where
    $f = \{0,1,...t-1\}$;
6)   if $t < F+1$ // no drop at time T_{F+1};
7) $dropped\_traffic(t) = sum(t) - capacity$;
8)   temp = $dropped\_traffic(t)$;
9)   for ($f = 0$; $f < $ t; f++)
10)   if $sum(f) \leq temp$
11)   for ($c = 0$; $c <= 2$; c++)
12) $d(c, f, t) = n(c, f, t)$;
13) $temp = temp - n(c, f, t)$;
14)   else if $sum(f) > temp$
15)   For ($c = 0$; $c <= 2$; c++)
16) $d(c, f, t) = temp * \frac{n(c,f,t)}{sum(f)}$;
17) $temp = 0$;
18) Output
   $revenue\ loss\ rate =$
   $(\sum_{t=0}^{F} \sum_{c=0}^{2} \sum_{f=0}^{F} \frac{r(c) \times d(c,f,t) \times pun(c,f)}{b(c)}) / revenue\_noleaving$

**Figure 3-4: Algorithm to calculate revenue loss rate
for Failure Approach**

3.4.5 Failure/Revenue/Bandwidth Combination Approach

Combination Approach selects VOD connections to be dropped by assigning values of priorities that are calculated using all three statistics: Failure, Revenue, and Bandwidth statistics. Customers with the lowest priorities are dropped first at each time T_t. Priority values assigned to (c, f)-*customers* are

expressed in terms of revenue loss per bandwidth and are calculated using the following equations:

the priority value of a $(c, f) - customer$: $w(c, f)$

$$= \begin{cases} \dfrac{r(c) \times pun(c,f)}{b(c)} \,, & if\ f \geq F' & --\text{I} \\[2ex] \dfrac{r(c) \times pun(c,f)}{b(c)} + \alpha \times (1 - pun(c,f) \times w(c, f+1)), & if\ f < F' & --\text{II} \end{cases}$$

The probability of customer leaving $pun(c, f)$ monotonically increases with the increasing number of interruptions that a customer has experienced and approaches 1 when f approaches F' (F' is a number big enough to ensure that for all customers, $pun(c, f) = 1,$ when $\geq F'$). When the probability $pun(c, f) = 1,$ it means that all customers who have experienced F' interruptions or more will definitely unsubscribe from the network if they get another interruption. Also, the priority value $w(c, f)$ increases monotonically with increasing values of $r(c)$, $pun(c, f)$ and $1/b(c)$. Formula I calculates the priority in terms of the revenue loss per bandwidth. The additional part in Formula II describes the change in assigned priority values caused by (c, f) -*customers* becoming $(c, f + 1)$ -*customers* after experiencing one more interruption; the priority value is $w(c, f + 1)$ if a (c, f)-*customer* does not unsubscribe, and this happens with probability $1 - pun(c, f)$. The size of this change in assigned priority values is adjusted using α ($0 \leq \alpha \leq 1$), a tuneable factor in Formula II, in the following two situations:

1) Different groups of (c, f)-*customers* receive the same priority value 0, regardless of revenue and bandwidth statistics. This situation happens when $pun(c, f) = 0$ for different groups of (c, f) -

customers because these (c, f) -*customers* can tolerate $f + 1$ interruptions;

2) Priority values happen to be the same for different groups of (c, f)-*customers* when $pun(c, f) \neq 0$.

Combination Approach can achieve a locally optimal solution at each time T_t by dropping connections with the least revenue loss per bandwidth, based on assigned priority values. Although the factor α is used to adjust the priority values of different groups of (c, f)-*customers* that are assigned the same priority values, the value of α is set to be small enough so that it does not change the priority rankings of the other groups of (c, f)-*customers* that do not receive the same priority values. If the value of α is too big, it may change the priority rankings of (c, f)-*customers* that are not assigned the same priority values, and as a result, Combination Approach can no longer guarantee a locally optimal solution at every time T_t. Therefore, the value of α is set to be very small (e.g. α=0.01 in our later experiments) in this project. The algorithm to calculate revenue loss rates for Combination Approach is shown in Figure 3-5.

1) data initialization;
2) calculate the priority values *w(c,f)* for *(c,f)-customers* and sort by increasing order of priority value.
3) for (t = 1; t <= F+1; t++)
4)   calculate the traffic $n(c, f, t)$ at time T_t for each c and f;
5)   calculate $sum(t) = \sum_{c=0}^{2} \sum_{f=0}^{t-1} n(c, f, t)$ at time T_t;
6)   if t < F+1   // no drop for t = F+1;
7) $dropped\_traffic(t) = sum(t) - capacity$;
8)   temp = $dropped\_traffic(t)$;
9)   for (i = 0; i <= j-1; i++)
10)   if $sum(c) \le temp$
11) $d(c, f, t) = n(c, f, t)$;
12) $temp = temp - n(c, f, t)$;
13)   else if $sum(c) > temp$
14) $d(c, f, t) = temp$;
15) $temp = 0$;
16) Output

$revenue\ loss\ rate =$

$(\sum_{t=0}^{F} \sum_{c=0}^{2} \sum_{f=0}^{F} \frac{r(c) \times d(c,f,t) \times pun(c,f)}{b(c)}) / revenue\_noleaving$

Figure 3-5: Algorithm to calculate revenue loss rate for Combination Approach

4. EXPERIMENTS AND PERFORMANCE COMPARISON

There are five predictor variables in our models: the number of failures in one experimental period (*F*), the probability that a (c)-*customer* is watching a VOD program $(pw(c))$, $Triple-ratio$, *revenue-ratio* between (c)-*customer*s, and the probability that a (c,f)-*customer* unsubscribes from the VOD service $(pun(c,f))$. To obtain the maximum information from our experiments, we conduct a 2^k factorial design and a full factorial design [43] to efficiently evaluate the effects of the five predictor variables and compare the performance of all our models. The findings from our experimental designs are informative to service providers. The software *Lingo* was used as the linear program solver for our LP model. Simulations for all our on-line models were coded in the C++ programming language; the simulations in [3] were also reproduced so that we can compare the performances of our approaches with those of their approaches. Results from the 2^k factorial experiments show that the number of failures *F* and the probability $pun(c,f)$ are the two most important predictor variables for the revenue loss rate. Findings from the full factorial experiments suggest that the linear programming model for Optimal Approach always outperforms other models and in this model, revenue loss can even be minimized to 0 in some cases. Among all of our on-line approaches, the performance of Revenue Approach is always the worst. Failure and Combination approaches perform as well as Optimal Approach in some cases and can even reduce the

revenue loss to zero at times. Although Combination Approach is designed to identify the locally optimal solution at each time that a failure occurs, Bandwidth Approach can achieve better performance than Combination Approach in some cases. By introducing bandwidth statistics, our approaches perform better than the approaches in [3] in our simulations. Specific case studies are also conducted,

(1) to examine the influence of α, the tuneable factor in Combination Approach, on customers' priority rankings;

(2) to determine why Optimal Approach always performs better than Combination Approach;

(3) to explain why and how the variable, $pw(c)$, the probability that a (c)-*customer* is watching a VOD program, is critical in helping to minimize the revenue loss to 0, even if it was not identified as a major predictor variable in the 2^k factorial experiment;

(4) to simulate three situations in which varying numbers of new customers arrive in each interval between two adjacent failures in order to learn how randomly occurring failures may affect revenue loss.

4.1 Background Description for Experiments

The experiments are designed based on the assumptions introduced in Section 3.2.2. We assume that the VOD service is provided in a simple point-to-point DWDM ring network with one centralized server and one distribution node, as shown in Figure 3-1. The fixed capacity on each link is 10Gb. There are three

different types of VOD programs, standard-definition (SD) VOD, DVD-quality video streams and high-definition (HD) VOD programs, which, on average, use bandwidths of 3.75Mbps, 9.8Mbps, and 19Mbps, respectively [42]. We only study the cases where the capacity of the surviving link cannot accommodate all the traffic in peak traffic time when a failure happens. Therefore, we assume that the total amount of the initial traffic is 10Gb, which is evenly distributed to the two point-to-point links so that half of the bandwidth of each link is occupied. Moreover, there are always new customers joining the network to ensure that the total traffic always exceeds the capacity of one link. The total number of failures for each experimental period determines the amount of traffic caused by new customers at each time T_t so that the total traffic at the end time T_{F+1} equals the full capacity of both links if no customers leave. For example, if there are 4 failures, the traffic for newly joined customers is 10Gb/5 = 2Gb at each interval between two adjacent failures; and the total traffic at the end time T_5 is 20Gb without any customer unsubscriptions. Performance results are calculated as the percentage of revenue loss.

4.1.1 Determination of values for predictor variables

We are very careful about the determination of values for all the predictor variables because without realistic value ranges, the findings on the impact of each predictor variable and the performance of each approach would be of little value. The values for the predictor variables were determined based on our more realistic assumptions and we discarded some arbitrary value assumptions in [3].

In Table 2, we compare our values and value ranges for the predictor variables with those used in [3].

Predictor Variables	Value Ranges in This Project	Value Ranges in [3]
A: number of failures	$F =[1,5]$	$F = [1,4]$
B: probability that a *(c)-customer* is watching a VOD program	$pw(c) =$ [{60%,60%,60%}, {90%,90%,90%}]	$pw(c) =$ [{50%,100%}, {14.29%,100%}]
C: *triple-ratio* of the number of *(c)-customers*	*Triple-ratio* = [5:3:1, 1:3:9]	Ratio= [5:1, 2:1]
D: *revenue-ratio* between *(c)-customers*	*Revenue-ratio* = [2:3:4, 2:6:10]	*Revenue-ratio* = [1:2, 1:7]
E: probability that a *(c, f)-customer* unsubscribes from the service	$pun(c,f) = [$ $\begin{pmatrix}0,0.2,0.3,1,1\\0,0.3,0.4,1,1\\0,0.4,0.5,1,1\end{pmatrix}, \begin{pmatrix}0.5,1,1,1,1\\0.5,1,1,1,1\\0.5,1,1,1,1\end{pmatrix}$ $]$	$pun(c,f) = [$ $\begin{pmatrix}0,1,1,1,1\\0,1,1,1,1\end{pmatrix}, \begin{pmatrix}0.5,1,1,1,1\\0.5,1,1,1,1\end{pmatrix}$ $]$

Table 2: List and comparison of values for predictor variables
(predictor variables are labelled from A to E).

The objective of our revenue focused semi-protection approaches is to minimize the revenue loss. The best performance we expect of our approaches is zero revenue loss. Therefore, we started our experiments with 1-failure cases and increased the number of failures F until it was impossible to get zero revenue loss in any approach. This criterion was satisfied when the number of failures was 5. Therefore, our experiments simulate cases from 1 to 5 failures.

A recent survey (2007) by Nielsen Media Research showed that more than 50% of households are watching TV programs during the television watching prime time (e.g. 8pm-11pm in U.S.). Typically, the peak traffic time is during the prime time and the network bandwidth is probably enough to support full protection for all traffic during off-peak times. We only examine the situation that one surviving link cannot accommodate all traffic when a failure happens during the peak traffic time. Thus we assume that the range of $pw(c)$ is from 60% to 90%. Only two cases were considered in [3]: in the first case, higher revenue customers watch the VOD programs with probability 100% and lower revenue customers watch with probability 50% (one day out of two); in the second case, higher revenue customers watch the VOD programs with probability 100% and lower revenue customers watch with probability 14.29% (one day per week). We assume that the probability for all customers watching VOD programs is the same during peak traffic time. Hence we assigned each customer the same probability $pw(c)$ in our experiments and the probability is always a value in the range from 60% to 90%.

In [3], the ratio of the numbers of two different classes of customers is in the range 5:1 to 2:1. Similar to the left end of their range: 5:1, our *triple-ratios* start at 5:3:1. To decide on the right end of the range of our *triple-ratios*, we referred to the findings of some recent surveys, which revealed that nowadays almost all replacement TV sets purchased are HDTV sets. We expect that in the near future, most customers will be watching HDTV programs and thus we set the right end of the range to be 1:3:9 for our experiments. Comparing the pricing

of current VOD services, which ranges from \$4 to \$13 per VOD order or from \$20 to \$100 subscription fees per month, we set the range for the values of *revenue-ratios* to be from 2:3:4 to 2:6:10.

In our experiments, we enlarged the value ranges for the predictor variable $pun(c, f)$, using a probability matrix to accommodate the possibility that customers may show more tolerance of network interruptions than the low tolerance (i.e., all customers will unsubscribe after experiencing the second interruption) assumed in [3]. Our values of $pun(c, f)$ also ensure that the probabilities for different *(c)-customers* reflect our assumption that $pun(c, f)$ indicates customers' expectations of the reliability of network services. The higher revenue customers may have higher expectations, and thus higher probabilities to unsubscribe from the service if they encounter service interruptions. In addition, we also studied the impact of two intermediate values,

$$pun(c, f) = \begin{pmatrix} 0,0.5,1,1,1 \\ 0,0.6,1,1,1 \\ 0,0.7,1,1,1 \end{pmatrix} \text{ and } pun(c, f) = \begin{pmatrix} 0.2,0.5,1,1,1 \\ 0.3,0.6,1,1,1 \\ 0.4,0.7,1,1,1 \end{pmatrix},$$ on the performance of our models in the full factorial experimental design.

4.2 2^k Experimental Design

In order to identify the impact of the five predictor variables, a 2^k experimental design was adopted to analyze the effects of the predictor variables and their interactions on revenue loss rate, using two levels of predictor variables: low and high. The 2^k experimental design reduces the total number of experiments needed for further analysis and ranks the importance of each

predictor variable in an efficient way, based on the proportion of the total variation attributed to each variable.

Following the 2^k experimental design procedures[43], with $k = 5$ (the number of predictor variables), we first set the two levels of each predictor variable, with the low level indicated by the sign, -1, and the high level indicated by the sign, 1, as shown in Table 3.

Impact Factors		Low Level	High Level
Number	**Notation**	**(sign: -1)**	**(sign: 1)**
A	F	1	5
B	$pw(c)$	{60%,60%,60%}	{90%,90%,90%}
C	$Triple-ratio$	5:3:1	1:3:9
D	$Revenue\ ratio$	2:3:4	2:6:10
E	$pun(c,f)$	$\begin{vmatrix} 0, 0.2, 0.3, 1, 1 \\ 0, 0.3, 0.4, 1, 1 \\ 0, 0.4, 0.5, 1, 1 \end{vmatrix}$	$\begin{vmatrix} 0.5, 1, 1, 1, 1 \\ 0.5, 1, 1, 1, 1 \\ 0.5, 1, 1, 1, 1 \end{vmatrix}$

Table 3: Levels and signs for the 5 predictor variables.

After we assigned levels and signs to the predictor variables, we conducted the experiments and used the experimental results from each approach to form a 32-equation set with 2^5 variables. The variables in the 32-equation set include all possible combinations of the 5 predictor variables so that all interactions between these predictor variables are examined. We labelled the

5 predictor variables from A to E as shown in Table 3. Thus, the impact variable AB stands for the interaction between A and B, the impact variable ABE stands for the interaction among A, B and E, and so on. We used the software *Lingo* to solve the 32-equation set and the results, the proportion of the total variation explained by each impact variable, are shown in Table 4. The order of the impact of all the impact variables is determined by the proportion of the total variation accounted for by each variable. As we can see from Table 4, the effects of all the second order and higher interactions are negligible because the total variation explained by these interactions is less than 1%, much smaller than that accounted for by the first order and primary impact variables, which are 15.92% and 83.75% respectively. The primary order variables A (the number of failures) and E (the probability of a customer leaving), which explained more than 93% of the total variation at the primary order in all six approaches, are identified as two major predictor variables. For example, for Optimal Approach, the proportion of explained variation by A and E is 96.12% of the total primary variation 83.75%; for Bandwidth Approach, it is 93.31%. In comparison, the effects of variable B (the probability of a customer watching VOD), C (the *triple-ratio*) and D (the *revenue-ratio*) are relatively minor and thus were not considered in our full factorial experimental design. It is worth noting that the impact of the five predictor variables on revenue loss rate varies by approach. For example, variable E is more influential than variable A in Optimal, Failure, and Combination approaches, but is less important than variable A in other approaches; the *revenue-ratio* has a minor effect in Revenue Approach, but no impact at all in

Failure and Random approaches. At the first order, the most significant interaction is AE, which accounted for 88% (14% out of 15.92%), 83%, 44%, 49%, 90%, and 85% of the total variation explained by all the 10 interaction first order variables in the six approaches respectively. The second most significant interaction is AB, which, at most, accounted for 22% of the total variation in Revenue Approach. Among all the approaches, the biggest variation explained by AE is 14%, whereas for AB, it is only 1.33%. Therefore, we only considered A and E as important predictor variables in our full factorial experimental design.

Factors	Optimal Approach	Random Approach	Revenue Approach	Bandwidth Approach	Failure Approach	Comb. Approach
Primary Effects	**83.75%**	**91.77%**	**93.09%**	**92.89%**	**86.51%**	**85.05%**
A	22.07%	45.10%	55.41%	56.86%	25.72%	25.75%
B	2.45%	3.35%	3.80%	3.59%	3.78%	3.67%
C	0.35%	0.05%	0.35%	0.18%	0.01%	0.40%
D	0.45%	0.00%	2.07%	1.35%	0.00%	0.33%
E	58.43%	43.27%	31.46%	30.91%	57.00%	54.90%
First order	**15.92%**	**8.07%**	**6.01%**	**6.37%**	**13.17%**	**14.40%**
AB	0.62%	1.06%	1.33%	1.29%	1.26%	1.28%
AC	0.06%	0.05%	0.18%	0.01%	0.01%	0.08%
AD	0.09%	0.00%	0.84%	0.60%	0.00%	0.04%
AE	14.00%	6.68%	2.65%	3.10%	11.79%	12.24%
BC	0.03%	0.00%	0.02%	0.03%	0.01%	0.05%
BD	0.01%	0.00%	0.04%	0.03%	0.00%	0.00%
BE	0.37%	0.23%	0.02%	0.08%	0.09%	0.12%
CD	0.14%	0.00%	0.59%	0.60%	0.00%	0.09%
CE	0.17%	0.05%	0.07%	0.39%	0.01%	0.07%
DE	0.43%	0.00%	0.27%	0.24%	0.00%	0.43%

	0.29%	0.15%	0.84%	0.72%	0.30%	0.47%
Second order	**0.29%**	**0.15%**	**0.84%**	**0.72%**	**0.30%**	**0.47%**
ABC	0.01%	0.00%	0.01%	0.01%	0.01%	0.02%
ABD	0.00%	0.00%	0.01%	0.01%	0.00%	0.00%
ABE	0.03%	0.10%	0.44%	0.23%	0.27%	0.20%
ACD	0.02%	0.00%	0.21%	0.27%	0.00%	0.00%
ACE	0.00%	0.05%	0.01%	0.10%	0.01%	0.01%
ADE	0.08%	0.00%	0.00%	0.01%	0.00%	0.08%
BCD	0.00%	0.00%	0.03%	0.01%	0.00%	0.00%
BCE	0.00%	0.00%	0.02%	0.00%	0.01%	0.02%
BDE	0.01%	0.00%	0.01%	0.00%	0.00%	0.01%
CDE	0.14%	0.00%	0.10%	0.08%	0.00%	0.13%
Third order	**0.03%**	**0.00%**	**0.06%**	**0.00%**	**0.01%**	**0.06%**
ABCD	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%
ABCE	0.01%	0.00%	0.02%	0.00%	0.01%	0.05%
ACDE	0.02%	0.00%	0.00%	0.00%	0.00%	0.01%
ABDE	0.00%	0.00%	0.03%	0.00%	0.00%	0.00%
BCDE	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Forth order	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**	**0.00%**
ABCDE	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Total	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**	**100.00%**

**Table 4: Importance of factors in each approach
in terms of proportion of the total variation.**

To summarize, results from our 2^k factorial experimental design suggest that among all the five predictor variables, the number of failures and the probability of customers unsubscribing from the VOD service are the most significant ones in terms of their impact on revenue loss rate. The changes in the

other three predictor variables, *triple-ratio*, *revenue-ratio* and the probability of a customer watching a VOD program, have little or no impact on revenue loss rate. One of the purposes of conducting 2^k factorial experiments is to improve the efficiency of our full factorial experiments by minimizing the number of predictor variables and thus the number of experiments. Based on the results from the 2^k factorial experiments, we examined the effects of the two major predictor variables only in the full factorial experiments: the number of failures and the probability of customers unsubscribing from the VOD service.

4.3 Two-factor Full Factorial Design

In our two-factor full factorial design, we extended the levels of the two major variables. For variable F, we examined five levels from 1 to 5, as opposed to 1 and 5 in the 2^k factorial experimental designs. For variable $pun(c, f)$, we added two more levels: $pun2(c, f)$ and $pun3(c, f)$, instead of just $pun1(c, f)$ and $pun4(c, f)$ in the 2^k factorial experimental designs. The increasing order of varying probabilities $pun(c, f)$ is $pun1 = \begin{pmatrix} 0,0.2,0.3,1,1 \\ 0,0.3,0.4,1,1 \\ 0,0.4,0.5,1,1 \end{pmatrix}$, $pun2 = \begin{pmatrix} 0,0.5,1,1,1 \\ 0,0.6,1,1,1 \\ 0,0.7,1,1,1 \end{pmatrix}$, $pun3 = \begin{pmatrix} 0.2,0.5,1,1,1 \\ 0.3,0.6,1,1,1 \\ 0.4,0.7,1,1,1 \end{pmatrix}$, and $pun4 = \begin{pmatrix} 0.5,1,1,1,1 \\ 0.5,1,1,1,1 \\ 0.5,1,1,1,1 \end{pmatrix}$. To examine the performance of all six approaches, the full factorial design requires $5 \times 4 \times 6 = 120$ experiments.

We also fixed the values of the three minor predictor variables as follow $pw(c) = (90\%, 90\%, 90\%)$, $triple - ratio = 5:3:1$, and $revenue\ ratio = 2:3:4$. Table 5 shows the performance results measured by the revenue loss rate

of all six approaches from the two-factor full factorial design. The impact of $pun(c, f)$ on revenue loss rate (%) at each level of F is depicted in Figure 4-1 to Figure 4-5.

		$F = 1$	$F = 2$	$F = 3$	$F = 4$	$F = 5$
Optimal Approach	$pun1$	0.00	0.00	0.00	0.56	3.16
	$pun2$	0.00	0.00	0.00	0.74	3.83
	$pun3$	5.61	10.11	13.83	16.88	19.25
	$pun4$	7.39	13.92	18.57	21.57	23.65
Random Approach	$pun1$	0.00	1.48	4.07	7.41	11.18
	$pun2$	0.00	3.10	8.26	14.16	19.78
	$pun3$	6.16	12.30	17.93	22.76	26.74
	$pun4$	11.25	20.27	26.86	31.49	34.75
Revenue Approach	$pun1$	0.00	4.20	9.62	19.24	27.43
	$pun2$	0.00	10.51	22.48	30.89	35.46
	$pun3$	6.85	17.83	29.04	36.78	41.03
	$pun4$	16.31	32.03	39.84	44.24	47.26
Bandwidth Approach	$pun1$	0.00	3.32	6.68	10.24	13.04
	$pun2$	0.00	5.81	10.49	13.66	16.01
	$pun3$	5.61	11.43	15.86	18.86	21.12
	$pun4$	7.39	15.05	19.54	22.34	24.55
Failure Approach	$pun1$	0.00	0.00	0.00	0.99	6.16
	$pun2$	0.00	0.00	0.00	2.07	12.91
	$pun3$	6.16	11.22	15.38	18.84	21.73
	$pun4$	11.25	19.13	24.76	28.90	31.99
Combination Approach	$pun1$	0.00	0.00	0.00	0.89	5.57
	$pun2$	0.00	0.00	0.00	1.55	9.84
	$pun3$	5.61	10.11	13.83	17.01	19.91
	$pun4$	7.39	13.92	18.74	22.32	25.01

Table 5: Revenue loss rate (%) of all the approaches in the full factorial design.
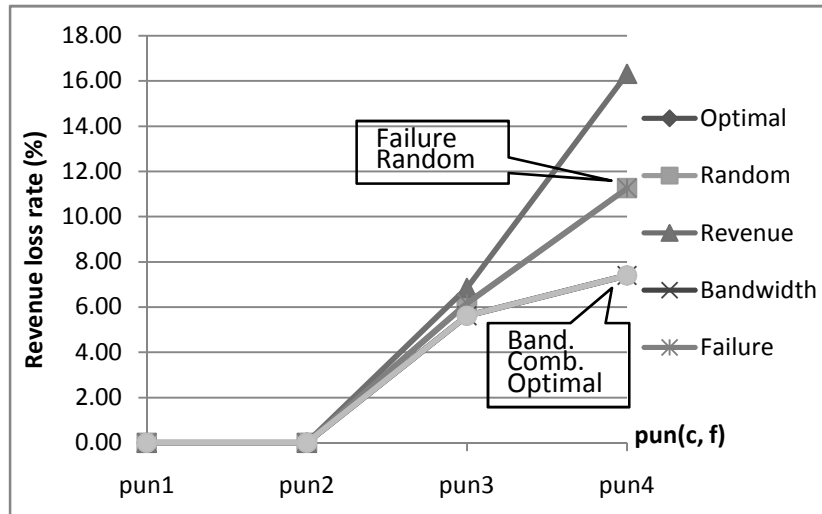
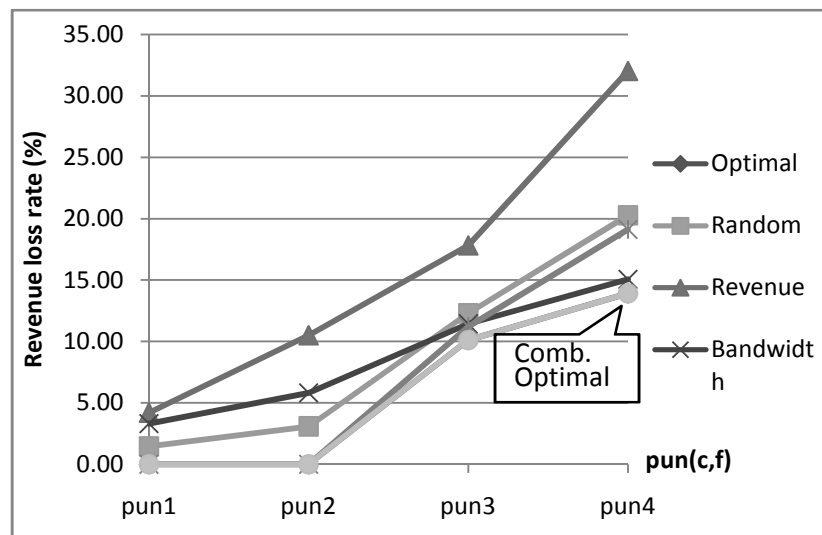**Figure 4-1: Revenue loss rate (%) when *F* = 1.**

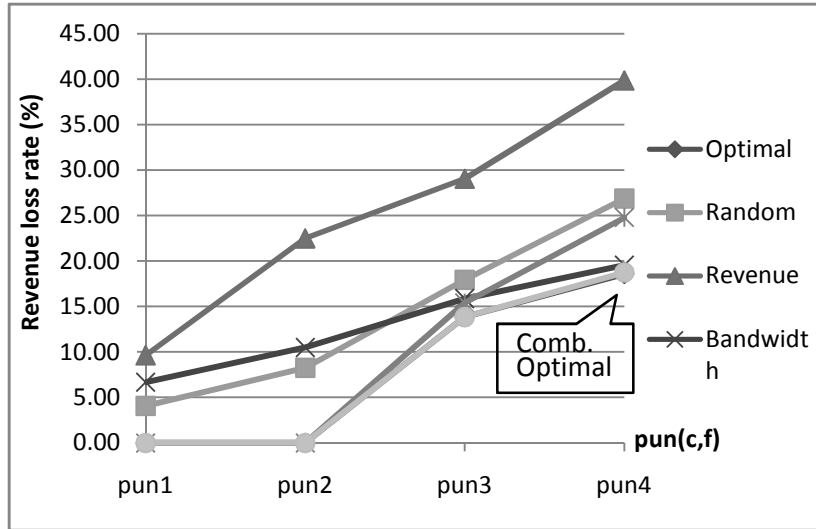**Figure 4-2: Revenue loss rate (%) when *F* = 2.**

58

Figure 4-3: Revenue loss rate (%) when *F* = 3.
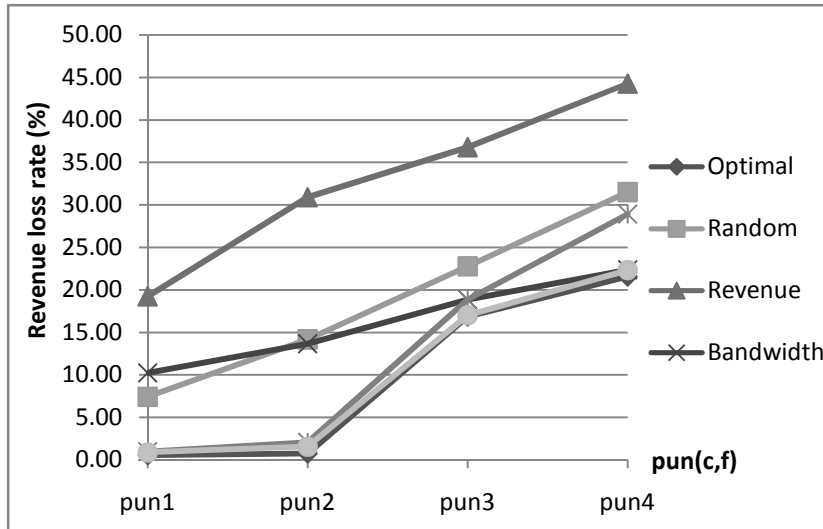
Figure 4-4: Revenue loss rate (%) when *F* = 4.
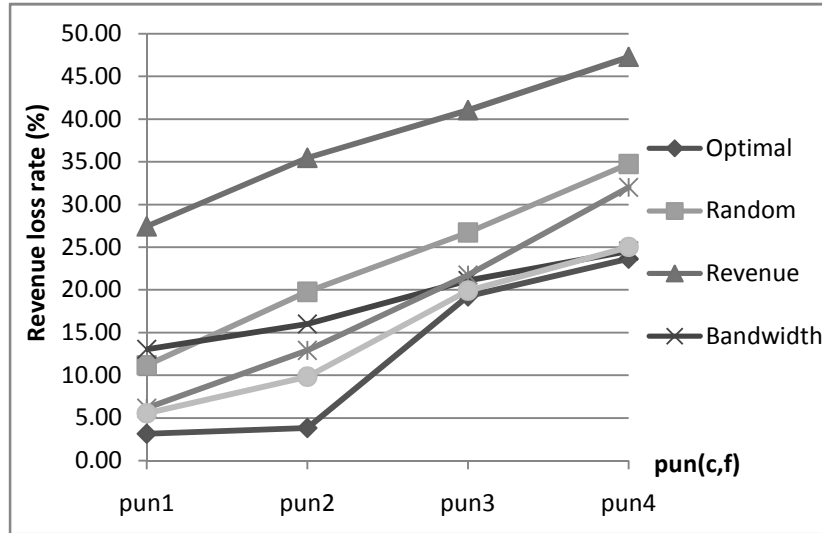
Figure 4-5: Revenue loss rate (%) when *F* = 5.

For $F = 1$, Figure 4-1 shows that in all approaches, the impact of $pun(c, f)$ on revenue loss rate follows similar trends: revenue loss rate is zero from $pun1$ to $pun2$ but increases afterwards with increasing $pun(c, f)$. The values of $pun1$ and $pun2$ indicate that all customers can tolerate the first interruption and will not unsubscribe from the service thereafter. To compare the performance of all the approaches, we should not rely on Figure 4-1 but focus on the results from the other four figures because there will be no revenue loss from $pun1(c, f)$ to $pun2(c, f)$ at the time when the first failure occurs, regardless of the approach used. With the number of failures F and the probability $pun(c, f)$ increasing, the revenue loss rates increase in all approaches, except in the following cases: revenue loss rate is zero from $pun1(c, f)$ to $pun2(c, f)$, when $F = 2$ or $F = 3$, in Optimal, Failure and Combination approaches .

After introducing bandwidth statistics, we found that Random Approach is not the worst approach in contrast to the findings in [3]. Instead, Revenue Approach is always the one with the highest revenue loss rate, which can be explained using the concept of revenue loss per bandwidth. As we mentioned in Section 3.4.5, the revenue loss per bandwidth is calculated using $\frac{r(c) \times pun(c,f)}{b(c)}$. Based on our more realistic assumptions about the values of $r(c), pun(c,f)$ and $b(c)$, the higher revenue customers always have lower revenue loss per bandwidth than the lower revenue customers. Revenue Approach chooses the VOD connections to be saved by always giving priority to higher revenue customers, which means it actually loses more revenue in total by dropping lower revenue customers who have higher revenue loss per bandwidth.

When $F > 1$, the performance trends of Random Approach and Bandwidth Approach are similar to that of Revenue Approach, which is approximately linear. If we simply consider their trends as linear, the slope of Bandwidth Approach is less steep than Random Approach and the revenue loss rate of Bandwidth Approach is slightly higher than that of Random Approach at $pun1$. However, when $F = 5$, the revenue loss rate of Bandwidth Approach is much less than that of Random Approach and is actually the least among all the off-line approaches at $pun4$. This finding is consistent with the result from the 2^k factorial design that in Bandwidth Approach, $pun(c,f)$ has less impact than in Random Approach.

Failure and Combination approaches show similar performance trends to Optimal Approach. We also found that the revenue loss rate in Failure and Combination approaches is zero whenever the revenue loss rate is zero in

Optimal Approach. All three approaches have much lower revenue loss rate than the other approaches when $F < 5$ and the probability $pun(c,f)$ is low, such as $pun(c,f) = pun1$ or $pun2$. This finding is understandable because both Failure and Combination approaches always first drop the connections of those customers who are less likely to unsubscribe from the service if their connections are dropped. Apparently, this is how Failure Approach determines the connections to be dropped. Combination Approach calculates priority values using $pun(c,f)$, and assigns lower priority to customers who have experienced fewer interruptions, especially those customers whose probability of unsubscribing is zero. We can also see in the five figures that there are sudden increases in the revenue loss rate in all three approaches when $pun(c,f)$ changes from $pun2$ to $pun3$ and their performances get close to the performances of the other approaches. This is caused by the fact that none of the three approaches can benefit from customers with low probabilities to unsubscribe at $pun3$ and $pun4$, where there are few customers who can tolerate even the first interruption.

4.4 Result Comparison with Previous Research

We compared the performance results of our approaches with the results in [3] and found that our approaches achieve better performance in terms of minimizing the revenue loss after introducing bandwidth statistics and using more realistic values for predictor variables.

The approaches we compared are the off-line Optimal approach and the two best on-line approaches in [3]: Failure and Combination approaches. Gerstel et al. [3] consider two groups of customers only and assumed that the two groups use the same amount of bandwidth (but did not specify the bandwidth explicitly). To make it comparable, we examined two classes of customers, high revenue customers (*(0)*-customers) and low revenue customers (*(1)*-customers), that on average occupy bandwidth 3.75Mbps and 19Mbps respectively in our approaches, and the same bandwidth was assigned for all the approaches in [3]. We re-simulate their approaches using the bandwidth of 10Mbps. The actual amount of bandwidth usage does not affect performance results because only the bandwidth usage ratio was used in all approaches. Values of the other predictor variables used for comparison were determined as follows: the total number of failures F is from 1 to 5; the ratio of the number of *(c)*-customers is 5:1; the *revenue-ratio* is 1:2; $pw(c) = \{50\%, 100\%\}$ for two classes of customers; and $pun(c,f) = \left(\begin{smallmatrix} 0.5,1,1,1,1 \\ 0.5,1,1,1,1 \end{smallmatrix} \right)$. In order to make it comparable to the approaches in [3], the values we chose are within the value ranges in [3].

The comparison results are shown in Figure 4-6, Figure 4-7, and Figure 4-8. From these three figures, we can conclude that the performance can be improved significantly by introducing the bandwidth statistics for Optimal and Combination approaches (e.g. 36.21% for Optimal Approach when $F = 5$). For Failure Approach, the performance of our model is almost the same as that in [3] because both models choose the same proportion of $(c,f)-$customers to be dropped; bandwidth statistics are not used to calculate the proportion of

$(c, f) - customers$ to be dropped --- the calculation is based only on failure statistics.
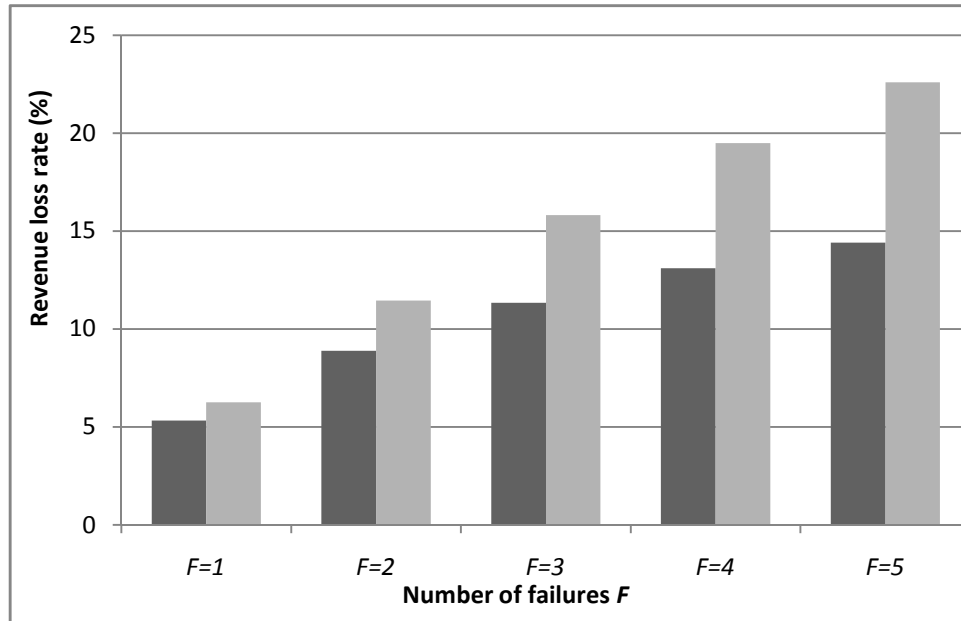

Figure 4-6: Revenue loss rate (%) comparison of our study (dark-color) with [3] (light-color) for Optimal Approach.
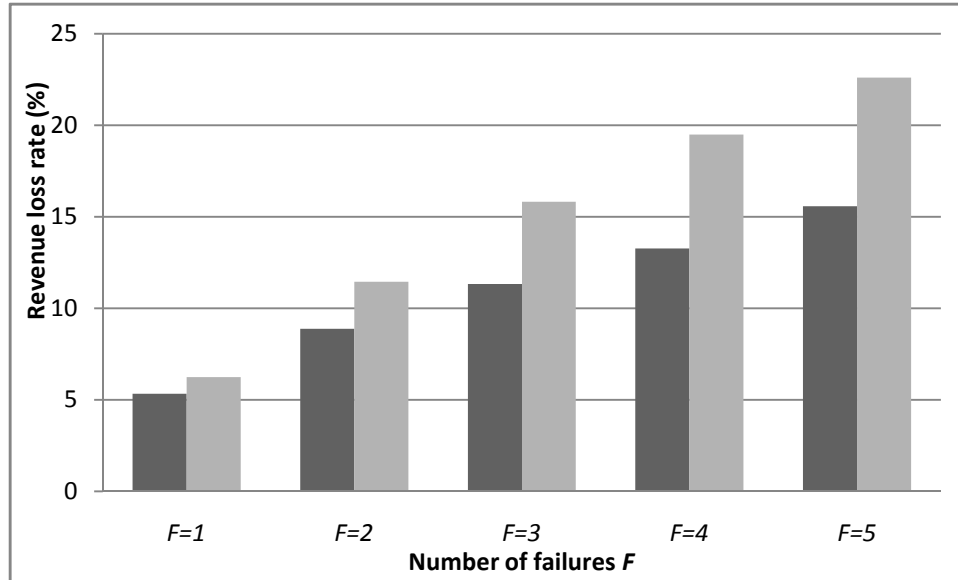
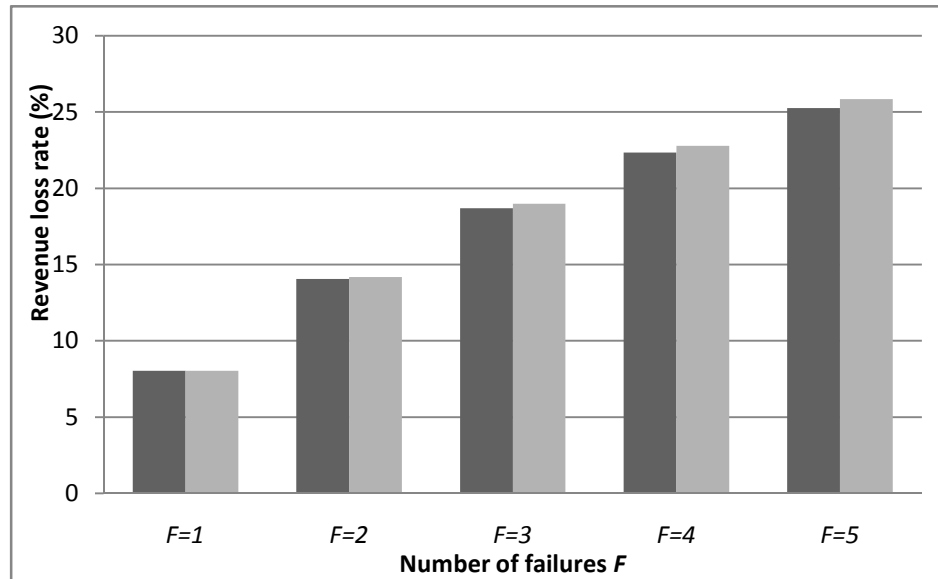**Figure 4-7: Revenue loss rate (%) comparison of our study (dark-color) with [3] (light-color) for Combination Approach.**

Figure 4-8: Revenue loss rate (%) comparison of our study (dark-color) with [3] (light-color) for Failure Approach.

4.5 Observations

We evaluated the impact of the five predictor variables using the 2^k factorial experimental design and compared the performance of all six approaches using the full factorial experimental design. In this section, we summarize our observations.

I.   Results from our study suggest that the two predictor variables --- the number of failures F and the probability of customers unsubscribing from the service $pun(c,f)$ --- and their interactions have significant effects on the performance of all the approaches.

II. Optimal Approach, as the only off-line approach, outperforms all the on-line approaches in all cases.

III. Combination Approach achieves the best overall performance among the on-line approaches by using locally optimal solutions.

IV. In most cases, Failure Approach performs as well as Combination Approach because both approaches always first drop the connections of those customers who are less likely to unsubscribe from the service if their connections are dropped.

V.   Optimal, Combination and Failure approaches can keep revenue loss at zero in the situations when all customers can tolerate at least one interruption. Whenever Optimal Approach can achieve zero revenue loss, so can Combination and Failure approaches.

VI.   Our results are quite different from the findings in [3]. In our study, Random Approach is not the worst approach. Instead, Revenue Approach performs the worst because it fails to optimize the selection of connections to be dropped. For example, between *(0,3,5)-customers* and *(2,0,5)-customers* at time T_5 , Revenue Approach chooses to drop the connections of *(0,3,5)-customers* who have lower revenue contributions but higher probability to unsubscribe, when in fact dropping the connections of *(2,0,5)-customers* leads to no revenue loss.

VII.   After adding bandwidth statistics, Bandwidth Approach proposed in this project can achieve the best performance of all on-line approaches.

VIII.   We extended the five approaches used in [3] by introducing bandwidth statistics. Compared with the approaches in [3], our approaches achieve better performance by further reducing the revenue loss rate by as much as 36%.

4.6 Specific Case Studies

4.6.1 Case 1: Impact of factor a in Combination Approach

In Section 3.4.5, we discussed that the different groups of (c, f)-*customers* may be assigned the same priorities in Combination Approach. To prevent this kind of situation, the tuneable factor α is used to take into account the priority of $(c, f + 1)$-*customers* to slightly adjust the priority of (c, f)-*customers*; $(c, f + 1)$-

customers are the (c, f)-*customers* whose connections are dropped by the *f+1*st interruption but they keep subscribing to the service. The side effects of *α* are: the calculation of priority values of (c, f) -*customers* are based on the consideration of the impact of future failures even when these future failures do not actually occur; *α* can radically change the priority ranking of (c, f)-*customers* in situations when (c)-*customers* are not assigned the same priorities without the adjustment of *α*. These side effects of *α* may influence Combination Approach in such a way that it cannot achieve the locally optimal solution at each time T_t using the order of priorities ranked by revenue loss per bandwidth. In this section, we analyze the effects of *α* on the performance of Combination Approach to provide guidelines on how to properly determine the value of *α* so that the side effects of *α* can be avoided. With increasing *α*, the impact of the priorities of $(c, f + 1) -customers$ on the priorities of $(c, f) -customers$ is also increasing in Combination Approach and leads to a reordering of the priority ranks of all customers, which may prevent Combination Approach from achieving the least revenue loss per bandwidth at each time T_t. We simulated this reordering of priority ranks by changing the value of *α* in two experiments, Experiment 1 and Experiment 2. The impact of *α* on the performance of Combination Approach is shown in Figure 4-9. The fixed values that we used for the other variables in the two experiments are shown in Table 6.

Experiment 1	Experiment 2
F=5	
pw(c)={0.9, 0.9, 0.9}	
triple-ratio = 5:3:1	
revenue-ratio = 2:3:4	
varying *α* = {0.01,0.05,0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9,1}	

Table 6: Values used in Experiment 1 and Experiment 2.
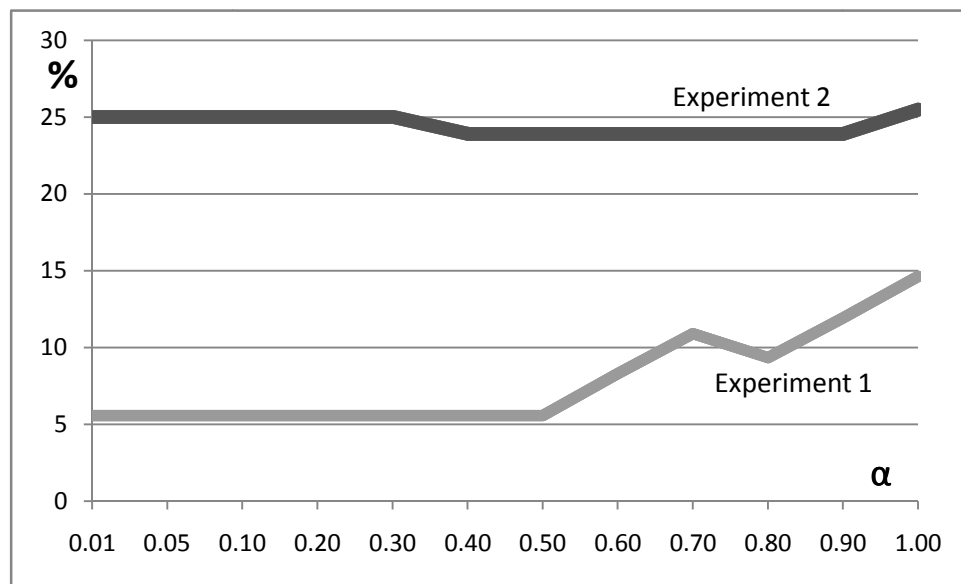

Figure 4-9: Revenue loss rate with varying *α*
in Experiment 1 and Experiment 2 with different values of   .

Combination Approach assigns lower priorities to   -*customers* with lower revenue loss per bandwidth to achieve locally optimal solutions at time   .

As shown in Figure 4-9, there are fluctuations in revenue loss rate as α varies in both Experiment 1 and Experiment 2. Each turning point in the figure indicates priority rank being reordered by changed α. When α is very low, for example, when $\alpha < 0.3$ in Experiment 2 and $\alpha < 0.5$ in Experiment 1, the priority values of (c, f)-*customers* are mainly determined by revenue loss per bandwidth. When $\alpha > 0.3$ in Experiment 2 and $\alpha > 0.5$ in Experiment 1, the priority values and thus the order of priority of (c, f)-*customers* have begun to be influenced by α, and do not reflect the order of priority determined solely by revenue loss per bandwidth. It is hard to expect a globally optimal solution from Combination Approach when its local solution is not optimal. However, as shown in Figure 4-9, we did see some improved global performance in Experiment 2. To figure out the reason for the improved performance, we conducted Experiment 3 and Experiment 4 to explain how α affects the revenue loss in Experiment 2 by reordering the priority rank. Different values of α were examined in the two experiments: α = 0.01 in Experiment 3 in order to show the priority rank without much influence of α, and α = 0.5 in Experiment 4 in order to show the priority rank influenced by α. Values of the other variables were the same as in Experiment 2. We show the priority ranks of the different groups of (c, f)-*customers* from these two experiments in Table 7 and the dropped traffic (Mb) and the revenue loss ($) at the time each failure happened in Table 8.

As we can see from Table 8, at the time when the first failure happens, the same amount of traffic (1667Mb) is dropped in the two experiments, and the same priority rank is used to choose (c,0)-*customers* to be dropped, which are

70

Priority Rank	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
α =0.01	(2,0)	(1,0)	(2,4)	(2,3)	(2,2)	(2,1)	(0,0)	(1,4)	(1,3)	(1,2)	(1,1)	(0,4)	(0,1)	(0,2)	(0,3)
α = 0.5	(2,0)	(2,4)	(2,3)	(2,2)	(2,1)	(1,0)	(1,4)	(1,3)	(1,2)	(1,1)	(0,0)	(0,4)	(0,1)	(0,2)	(0,3)

**Table 7: Priority ranks for *(c,f)*-customers
in Experiment 3 (α =0.01) and Experiment 4 (α =0.05).**

		$1st$ Failure	$2nd$ Failure	$3rd$ Failure	$4th$ Failure	$5th$ Failure	revenue loss rate in total
α =0.01	dropped traffic (Mb)	1667	2583	3088	3365	3517	25.01%
	revenue loss ($)	175	287	439	489	513	
α =0.5	dropped traffic (Mb)	1667	2583	2948	2616	2897	23.91%
	revenue loss ($)	175	305	504	401	435	

**Table 8: Dropped traffic and revenue loss comparison
between Experiment 3 (α =0.01) and Experiment 4 (α =0.05).**

(2,0), (1,0) and (0,0)-*customers* from low to high. At the time when the second

failure happens, the traffic (2583Mb) is dropped in Experiment 3 in order of rank

from the (2,0), (1,0), (2,1), (0,0), (1,1), (0,1)-*customers*, whereas the same

amount of traffic is dropped in order of rank from the (2,0), (2,1), (1,0), (1,1),

(0,0), (0,1) -*customers*. At this time, compared with Experiment 4 ($305),

Experiment 3 has better performance ($287) in terms of revenue loss. However,

according to the probability of a customer unsubscribing from the VOD service,

the customers who occupy more traffic load than those in Experiment 3

unsubscribe from service in Experiment 4. Therefore, at the time when the 3rd

failure happens, less traffic (2948Mb) needs to be dropped in Experiment 4 than

in Experiment 3 (3088Mb). The same reason explains why less traffic (2616Mb,

and 2897Mb) needs to be dropped in Experiment 4, which, in turn, explains why

there is less revenue loss in Experiment 4 ($401 and $435) than in Experiment 3

($489 and $513), at the times when the 4th and 5th failures happen. This can also

help us to understand why at the end time T_6, the total revenue loss rate is

smaller in Experiment 4 (23.91%) than in Experiment 3 (25.01%).

It is worth pointing out that when $\alpha = 1$, equation II in Section 3.4.5 can be

simplified to $w(c,f) = \frac{r(c)}{b(c)} \times pun(c,f) + \frac{r(c)}{b(c)} \times \left(1 - pun(c,f)\right) = \frac{r(c)}{b(c)}$. Therefore,

the priority values are constant for (c)-customers regardless of the failure

statistics f. In this case, Combination Approach selects connections to be

dropped randomly.

Based on the above observations, we recommend that the values of α

should be small enough to avoid the unwanted side effects when Combination

Approach is used. If we do not pay attention to the control of the value of α,

Combination Approach will work like an off-line approach by considering the

impact of the future failures that may not actually occur. Therefore, we use $\alpha =$

0.01 in our experiments.

4.6.2 Case 2: A case study to compare Optimal with Combination

Based on results from the full factorial design, we have concluded that Optimal Approach achieves the best global performance among all the approaches whereas the performance of Combination is worse than Optimal by using locally optimal solutions. To explain why there is this performance difference between Optimal and Combination, we conducted Experiment 5 to show the dropped traffic (Mb) and the revenue loss ($) of the two approaches at each time when a failure happens. The results are shown in Table 9.

The values of variables used in Experiment 5 are: $F = 5$, *(c)-customer triple-ratio* = 5:3:1, *revenue-ratio* = 2:3:4, $pw(c) = \{90\%, 90\%, 90\%\}$, and

$$pun(c, f) = \begin{pmatrix} 0.5,1,1,1,1 \\ 0.5,1,1,1,1 \\ 0.5,1,1,1,1 \end{pmatrix}.$$

		$1st$ Failure	$2nd$ Failure	$3rd$ Failure	$4th$ Failure	$5th$ Failure	Revenue Loss Rate in Total
Optimal	dropped traffic (Mb)	1667	2583	2750	2774	2930	23.65%
	revenue loss ($)	175	351	420	430	423	
Combination	dropped traffic (Mb)	1667	2583	3088	3365	3517	25.01%
	revenue loss ($)	175	287	439	489	513	

Table 9: Dropped traffic and revenue loss comparison when each failure happens.

When the 1st failure happens, both approaches drop the same customers with the same amount of traffic (1667Mb), thus they both have the same revenue

loss (\$175). When the 2nd failure happens, both approaches drop the same amount of traffic (2583Mb). Based on a locally optimal solution, the revenue loss for Combination Approach is \$287, whereas Optimal, based on a globally optimal solution, drops different $(c, f) - customers$ and loses more revenue (\$351). Although Optimal Approach loses more revenue at the time when the 2nd failure happens, it reduces the total amount of the traffic to be dropped for the 3rd, 4th, and 5th failures by dropping different $(c, f) - customers$. Therefore, the total revenue loss rate for Optimal Approach (23.65%) is less than that for Combination Approach (25.01%) at the end time T_6.

4.6.3 Case 3: A case study on the predictor variable $pw(c)$

Failure, Combination and Optimal approaches, as we found in the full factorial design, achieve better performance by dropping customers who can tolerate the first several interruptions or have not experienced any interruptions: there is no revenue loss when choosing to drop the connections of these customers. The value of $pw(c)$ is very informative in this regard: lower $pw(c)$ suggests that there are more customers who are not watching the VOD programs and thus have experienced none or fewer interruptions; when $pw(c)$ is low enough, there are enough such customers to enable an approach (such as Failure, Combination and Optimal) to achieve zero revenue loss by dropping the connections of these customers every time that a failure occurs. Therefore, although only a minor effect of the predictor variable $pw(c)$ on the performance of all approaches in the 2^k factorial design was found, we closely examined the contribution of $pw(c)$ to the zero revenue loss in Failure, Combination and

Optimal approaches in Experiment 5. The values of variables used in Experiment 5 are as follows: $F = \{1,2,3,4,5\}$; *(c)-customer triple-ratio* = 5:3:1; *revenue-ratio* = 2:3:4; $\mathrm{pun}(c,f) = \begin{pmatrix} 0,0.5,1,1,1 \\ 0,0.6,1,1,1 \\ 0,0.7,1,1,1 \end{pmatrix}$; $\mathrm{pw}(c)$ = {60%, 70%, 80%, 90%}. The revenue loss rates for the three approaches are shown in Figure 4-10, Figure 4-11, and Figure 4-12.
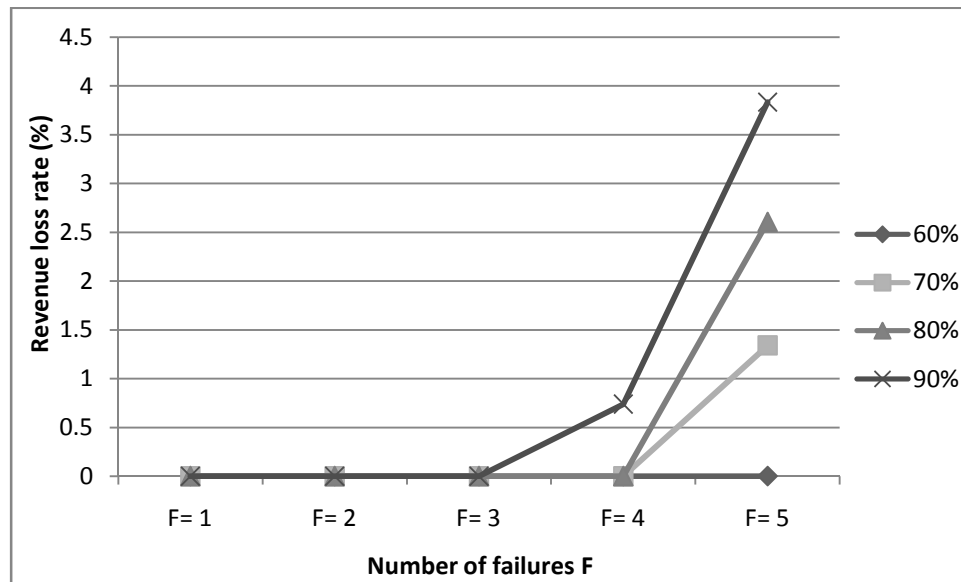

Figure 4-10: Performance of Optimal Approach with varying $pw(c)$.
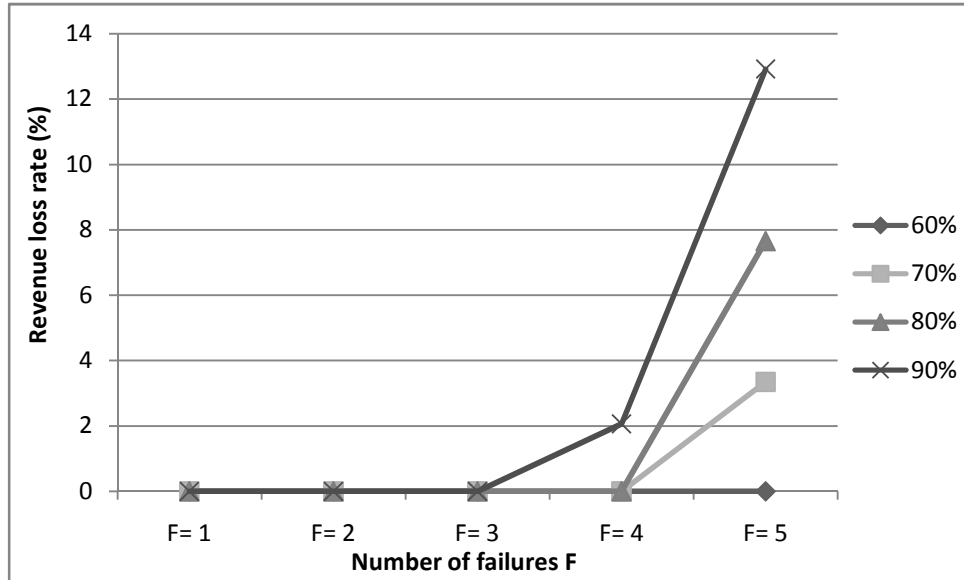
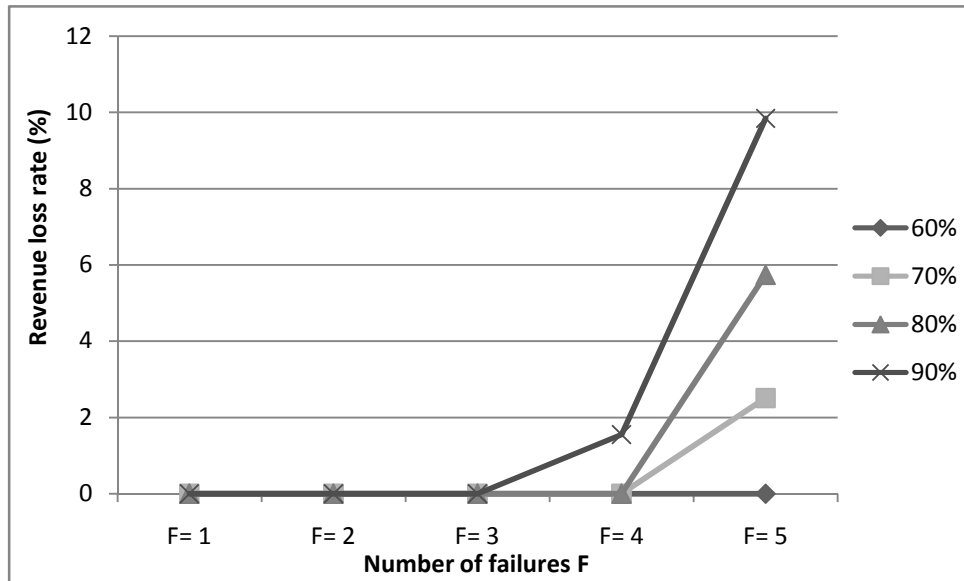**Figure 4-11: Performance of Failure Approach with varying $pw(c)$.**

Figure 4-12: Performance of Combination Approach with varying $pw(c)$.

As expected, these three approaches show similar performance trends: none of the performance trends in the figures are linear; all three approaches can

achieve zero revenue loss after the first several network failures, and there are sudden increases in revenue loss rate with increasing number of failures. More importantly, we can see the different influences of different values of $pw(c)$ from high to low. When $pw(c)$ is 90%, all the approaches can keep the revenue loss to zero for up to three failures. When $pw(c)$ is 80% and 70%, all the approaches can keep the revenue loss to zero for up to four failures. When $pw(c)$ is 60%, all the approaches can keep the revenue loss to zero for up to five failures. It is interesting to note that when $pw(c)$ is 60%, the revenue loss rate can be kept at zero for up to 5 failures even though $pun(c, f)$ suggests that there will be customers unsubscribing from the VOD service and thus revenue loss, if the customers experience the second interruption.

4.6.4 Case 4: A case study for the time when failures happen

As mentioned in Section 3.2.2, we assume that there is a constant number of new customers joining in the VOD service in each interval between two adjacent failures, which implies that the failures are distributed evenly within the real time period. Acknowledging that this assumption does not closely reflect what happens in reality, its influence on the performance of all the approaches is expected to be similar and thus does not affect our comparison of the approaches in any significant way. To validate this expectation, we conducted Experiment 6 and compared the performance of all six approaches in three simulated situations with different failure distributions, assuming that all the new customers are evenly distributed across real time intervals (each real time interval could be a week, a month, etc.).

The three different failure distributions are:

In Simulation 1, F-1 failures occur at time T_0 and the last failure happens at time T_F. Therefore, before the F-1st failure no VOD connections are dropped because no new customers join the network at time T_0. The amount of traffic, which is equal to $\frac{L \times F}{F+1}$, caused by new customers joining the network between the F-1st failure and the Fth failure is dropped at time T_F when the last failure occurs;

In Simulation 2, the failures are evenly distributed in the operation period;

In Simulation 3, all failures occur at time T_F.

It is important to note that in all three simulations, time T_F refers to the same time in real time to facilitate comparison: the amount of traffic caused by new customers joining the network before time T_F is the same in all three different scenarios. So in Case 4, two extreme simulations are examined. In Simulation 1, most new customers join the network after the F-1st failure but before the Fth failure; in Simulation 3, most new customers join before the first failure.

The values of variables used in Experiment 6 are: F = 5, *(c)-customer triple-ratio* = 5:3:1, *revenue-ratio* = 2:3:4, $pw(c) = \{90\%, 90\%, 90\%\}$,

and $pun(c,f) = \begin{pmatrix} 0.5,1,1,1,1 \\ 0.5,1,1,1,1 \\ 0.5,1,1,1,1 \end{pmatrix}$.

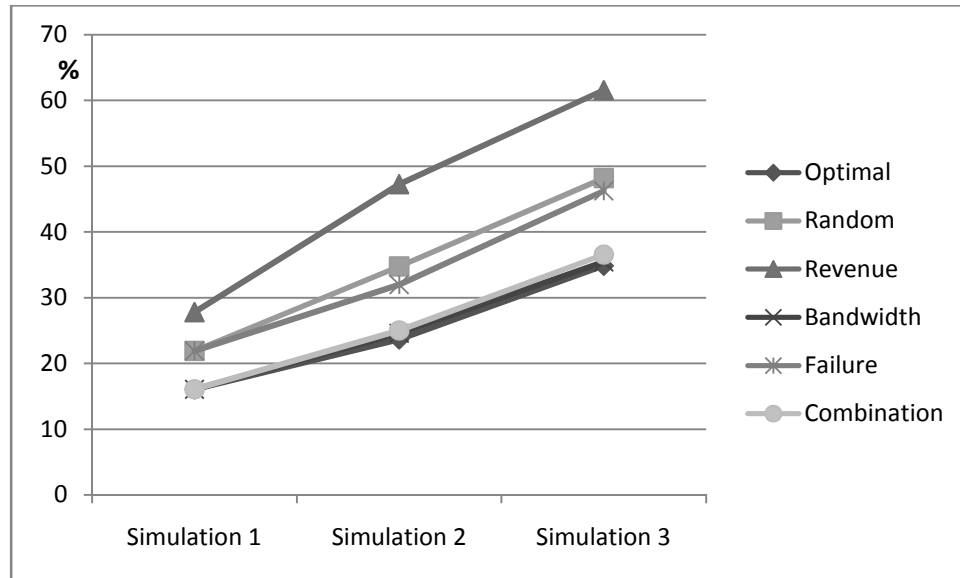The results from the three simulations are shown in Figure 4-13.

Figure 4-13: Comparison of the influence of different failure distributions.

As we can see in Figure 4-13, the performances of the approaches are different depending on the different failure distributions, but the relative performances of the approaches remain the same as discussed in our previous experimental analysis and are not affected by different failure distributions. The performance is better in Simulation 1 than in Simulation 2 and 3 because when most failures are concentrated in the early time section of the experimental period, VOD connections of fewer customers need to be dropped when a failure occurs during that early time period; due to the fact that most new customers joined after the concentrated failure period in Simulation 1, there are more customers who have not experienced any interruptions when it comes to the few failures in the later stages. This helps to reduce revenue loss because if the connections of these customers are dropped by these later failures, there is less revenue loss.

4.7 Time Cost Analysis

The connections that have been selected to be saved must be reassigned a wavelength in the surviving link within a very short period so that the customers will not think they are interrupted. For example, a customer can tolerate a very short interruption that lasts for less than 1 second and will not perceive it as an "interruption". Therefore, time cost must be examined and controlled quickly.

Time cost consists of two major parts, which can be controlled within an acceptable range on the order of milliseconds.

a.) The time complexity of selecting $(c, f) - customers$ to be dropped is $O(c \times F)$. To drop connections one by one, we must scan all (c, f)-*customers* (e.g. by looking at customer IDs), which leads to linear time cost *O(N)* where *N* is total number of customers. Normally, the number of customers may be up to tens of thousands in a 10Gb bandwidth channel. Then based on the calculation speeds of currently popular computers, the linear time cost is on the order of milliseconds.

b.) The time cost of reassigning the connections that have been selected to be saved on a wavelength in the surviving link can be minimized in 20 milliseconds [44], which is considered acceptable.

5. CONCLUSIONS AND FUTURE WORK

In this project, we reviewed two major problems in cost-effective DWDM networks: routing and wavelength assignment problem and traffic grooming problem. Our objective is to minimize the cost either by minimizing the number of wavelengths or SADMs to satisfy network connection requests, or by maximizing the network throughput given certain wavelengths.

To minimize the revenue loss by selectively saving VOD connections when a failure occurs in a DWDM network, we developed revenue focused semi-protection approaches based on more realistic assumptions about DWDM ring networks than those in [3]. Three statistics are used in our approaches: revenue statistics, failure statistics, and bandwidth statistics. Our approaches can be easily modified to adapt to real applications with real statistics. Our approaches can also be applied to other network services that continuously occupy large amounts of bandwidth, such as VOIP telephony, video conference service, and web-based video services.

We used 2^k and full factorial experimental designs to examine the impact of predictor variables and the performance of our approaches. Results from these studies suggest that even in a network with relatively low reliability, it is possible to minimize the revenue loss or even reduce it to zero when failures happen in the network without full protection. For example, in this study, we found that a network could allow up to five failures during peak traffic time without

any revenue loss. By introducing bandwidth statistics, our approaches perform better than those in [3]. Moreover, the new approach --- Bandwidth Approach --- proposed in this project can achieve the best performance among all of the on-line approaches.

In this project, we provide network operators with guidelines about how to minimize the cost and improve the efficiency of their DWDM networks through a review of current optimal solutions to RWA and traffic grooming problems. By determining the relative importance of the five predictor variables and the performance of the six semi-protection approaches, we also offer some insights into how to minimizing revenue loss in their VOD service.

Future work can be done to explore semi-protection schemes for multicast traffic patterns in DWDM networks. Multicast traffic models enable multiple customers (or nodes) in a network to share common wavelengths with the same or different VOD content. Moreover, as shown in [45], VOD connections of customers who are ordering the same popular VOD program within a short time window can be "batched" into one video stream to enable more customers to share the same wavelength in a DWDM network. How to selectively save VOD connections of customers in such a DWDM network with multicast traffic patterns when failures happen is a complicated and challenging research question. We expect that by properly rerouting and reassigning wavelengths, we can increase the level of protection of the network while at the same time minimizing revenue loss.

BIBLIOGRAPHY

[1]   "14 Tbps over a Single Optical Fiber: Successful Demonstration of World's Largest Capacity," Nippon Telegraph and Telephone Corporation, Sep. 2006. http://www.ntt.co.jp/news/news06e/0609/060929a.html.

[2]   O. Gurel, C. Mas, I. Tomkos, "Requirements for a Transparent Pan-European Network," Transparent Optical Networks, Proc., 6th International Conference, Vol. 1, pp.97-100, 2004.

[3]   O. Gerstel, G. Sasaki, A. Balasubramanian, "Revenue Focused Protection for VOD in DWDM rings," INFOCOM, 26th IEEE International Conference on Computer Communications, pp. 179-187, 2007.

[4]   http://www.cisco.com, website of Cisco Systems Inc., Jan. 2007.

[5]   http://www.huawei.com, website of Huawei Technologies Co. Ltd., 2008.

[6]   G. Giambene, Queuing Theory and Telecommunications: Networks and Applications, Springer Science, New York, pg. 47, 2005.

[7]   D. Barrett, T. King, Computer Networking Illuminated, Jones and Bartlett Publishers, ISBN 0-7637-2676-1, pg. 4, 2005.

[8]   "Introducing DWDM", Cisco Documentation, Cisco Systems Inc., 2000. http://www.cisco.com/univercd/cc/td/doc/product/mels/dwdm/dwdm_fns.htm#39797.

[9]   O. Gerstel, P. Lin, G. Sasaki, "Combined WDM and SONET Network Design," in Proc. IEEE Infocom, pp. 734-743, 1999.

[10] M. Sridharan and A. K. Somani, "Revenue Maximization in Survivable WDM Networks," in Proc. Optical Networking and Communications, SPIE, Vol. 1B, pp. 1012-1016, 1999.

[11] O. Gerstel and R. Ramaswami, "Optical Layer Survivability — a Service Perspective," IEEE Communications Magazine, Vol. 38, pp. 104 – 113, Mar. 2000.

[12]   Taehan Lee, Kyungsik Lee, and Sungsoo Park, "Optimal Routing and Wavelength Assignment in WDM Ring Networks," IEEE Journal on Selected Areas in Communications, Vol. 18, No. 10, pp. 2146-2154, Oct. 2000.

[13] N.Wauters and P. Demeester, "Design of the Optical Path Layer in Multiwave-length Cross-connected Networks," IEEE Journal on Selected Areas in Communications, Vol.14, pp. 881–892, 1996.

[14] R. Ramaswami, K. N. Sivarajan, Optical Networks: A Practical Perspective, 2nd Edition, San Mateo, CA, Morgan Kaufmann, pg. 455, 1998.

[15] B. Chen, G. N. Rouskas, R. Dutta, "Traffic Grooming in WDM Ring Networks to Minimize the Maximum Electronic Port Cost," Optical Switching and Networking, Vol.2, Issue 1, pp. 1-18, May 2005.

[16] G. Wilfong, P. Winkler, "Ring Routing and Wavelength Translation," in Proceedings of the 9th Annual ACM-SIAM Symposium on Discrete Algorithms, pp. 333–341, 1998.

[17] M. Garey, D. Johnson, G. Miller, and C. Papadimitriou, "The Complexity of Coloring Circular Arcs and Chords," SIAM Journal on Algebraic Discrete Methods, pg. 216–227, 1980.

[18] R. Ramaswami and K. N. Sivarajan, "Routing and Wavelength Assignment in All-optical Networks," IEEE/ACM Transactions on Networking, Vol. 3, pp. 489–500, Oct. 1995.

[19] C. Chen, S. Banerjee, "A New Model for Optimal Routing and Wavelength Assignment in Wavelength Division Multiplexed Optical Networks," in Proc. IEEE Infocom '96, pp. 164–171, Apr. 1996.

[20] K. C. Lee and V. O. K. Li, "A Wavelength Routing Algorithm in Wide-area All-Optical Networks," Journal of Lightwave Technology, pp. 1218–1229, Vol. 14, June 1996.

[21] N.Wauters and P. Demeester, "Design of the Optical Layer in Multi-wavelength Cross-connected Networks," IEEE Journal on Selected Areas in Communications, Vol.14, pp. 881–892, June 1996.

[22] T. Erlebach and K. Jansen, "The Maximum Edge-disjoint Paths Problem in Bidirected Trees," SIAM Journal on Discrete Mathematics, Vol. 14, pp. 326–366, 2001.

[23] P. Saengudomlert, E. H. Modiano, R. G. Gallager, "Dynamic Wavelength Assignment for WDM All-Optical Tree Networks," IEEE/ACM Transactions on Networking, Vol 13, No. 4, pp. 895-905, Aug. 2005.

[24] R. Datta, B. Mitra, S. Ghose, I. Sengupta, "An Algorithm for Optimal Assignment of a Wavelength in a Tree Topology and its Application in WDM Networks," IEEE Journal on Selected Areas in Communications, Vol. 22, No. 9, pp. 1589-1600, Nov. 2004.

[25] A. Tucker, "Coloring a Family of Circular Arcs," SIAM Journal on Applied Mathematics, Vol. 29, No. 3, pp. 493 – 502, 1975.

[26] I. A. Chlamtac, Ganz, and G. Karmi, "Lightpath Communications: An Approach to High Bandwidth Optical WAN's," IEEE/ACM Transactions on Networking, Vol. 40, pp. 1171–1182, 1992.

[27] D. K. Hunter and D. Marcenac, "Optimal Mesh Routing in Four-Fiber WDM Rings," Electronics Letters, Vol. 34, No.8, pp. 796–797, 1998.

[28] Y. Xiong, Q. Zeng, Y. Cheng, Y. Zhou, "Wavelength Requirements in Wavelength-Routed Ring Networks," Communications, Vol. 1, pp. 15-18, 1999.

[29] C. Nomikos, A. Pagourtzis, and S. Zachos, "Minimizing Request Blocking in All-optical Rings," In Proc. of the 2003 IEEE INFOCOM, Vol. 2, pp. 1355-1361, Apr. 2003.

[30] P. J. Wan and L. Liu, "Maximal Throughput in Wavelength-Routed Optical Networks," DIMACS Series in Discrete Mathematics and Theoretical Computer Science, Vol. 46, pp. 15–26, 1998.

[31] J.Q. Hu. "Optimal Traffic Grooming for Wavelength-division-multiplexing Rings with All-to-all Uniform Traffic," OSA Journal of Optical Networks, Vol. 1, No. 1, pp. 32–42, 2002.

[32] O. Gerstel, G. Sasaki, and R. Ramaswami, "Cost Effective Traffic Grooming in WDM rings," IEEE/ACM Transactions on Networking, Vol. 8, pp. 618-630, Oct. 2000.

[33] O.Gerstel, P. Lin, and G. Sasaki, "Wavelength Assignment in a WDM Ring to Minimize Cost of Embedded SONET Rings," INFOCOM'98. Seventeenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE Vol. 1, pp.94-101, 1998.

[34] L. Liu, X. Li, P. Wan, O. Frieder, "Wavelength Assignment in WDM Rings to Minimize SONET ADMs," INFOCOM 2000, Vol. 2, pp. 1020-1025, 2000.

[35] R. Dutta and G. N. Rouskas, "On Optimal Traffic Grooming in WDM Rings," Proceedings of the 2001 ACM SIGMETRICS, pp. 164-174, 2001.

[36] R. Dutta and G. N. Rouskas, "Traffic Grooming in WDM Networks: Past and Future," IEEE Network, Vol. 16, pp. 46-56, Nov./Dev. 2002.

[37] J. Q. Hu, "Traffic Grooming in Wavelength-division-multiplexing Ring Networks: a Linear Programming Solution," Journal of Optical Networking, Vol. 1, No. 11, pp. 397–408, Nov. 2002.

[38] N. Brauner, Y. Crama, G. Finke, P. Lemaire and C. Wynants, "Approximation Algorithms for the Design of SDH/SONET networks," RAIRO Operations Research, pp. 235–247, 2003.

[39] O. Goldschmidt, D.S. Hochbaum, A. Levin and E.V. Olinick, "The SONET Edge-partition Problem," Networks, Vol. 41, pp. 13–23, 2003.

[40] Y. Wang, Q.P. Gu, "Grooming of Symmetric Traffic in Unidirectional SONET/WDM Rings," in Proceedings of IEEE ICC'06, pp. 2407-2414, 2006.

[41] Y. Wang, Q.P. Gu, "On the Complexity and Algorithm of Grooming Regular Traffic in WDM Optical Networks," Journal of Parallel and Distributed Computing, Vol. 68, pp. 877-886, 2008.

[42] IXIA Leader in IP Performance Testing, "IPTV – Video Server Testing," 2006.
http://www.ixiacom.com/library/test_plans/display?skey=video_server.

[43] R. Jain, Art of computer Systems Performance Analysis Techniques For Experimental Design Measurements Simulation and Modeling, Wiley computer Publishing, John Wiley & Sons, Inc., 1991.

[44] X. Qin, and Y. Yang, "Multicast Connection Capacity of WDM Switching Networks With Limited Wavelength Conversion," Networking, Vol. 12, Issue 3, pp. 526-538, June 2004.

[45] S. Kulkarni, "Bandwidth Efficient Video-on-demand Algorithm (BEVA)," in Proc. of International Conference on Telecommunications, Vol 2, pp. 1335-1342, 2003.