

Assessing Network Service Profitability: Modeling from Market Science Perspective

Jin Xiao, *Student Member, IEEE*, and Raouf Boutaba, *Senior Member, IEEE*

Abstract—The prevalence of networked applications creates enormous earning potential for network service providers, who regularly conduct network planning and upgrade processes to keep their businesses profitable. Because the ability of a provider to retain and grow its customer population has an immediate impact on profit, the effectiveness of a network upgrade/planning strategy is intrinsically tied to the resulting changes in customer behavior. This paper examines the crucial linkage between network performance, customer satisfaction and profitability of network service, and presents an analytical modelling approach from market science perspective. Following this approach, we derive a generalized analytical forecasting model that projects service profitability from the underlying network service infrastructure and the subscriber population. Its construction is grounded on a number of influential theories in market science, economics and psychology, with emphasis on the particularities of network service operations. Through analysis and simulation studies, we show how such approach captures key factors and trends influencing service profitability and how it can significantly improve the network planning and upgrade processes.

Index Terms—economics, network design and planning, network applications and services

I. INTRODUCTION

The prevalence of networked applications in business operations and daily lives creates enormous earning potential for network service providers (SPs) and at the same time, fierce competition. Facing a consumer market with rising demands for quality and impending saturation, SPs are struggling to keep their customers satisfied and their businesses profitable. In essence, the SPs must execute strategies that maximize service profitability. The process of network planning and upgrades are essential facilitators of this objective.

In the network service industry, network planning and upgrades are regularly exercised. The practice is mostly ad hoc, where investment decisions are made based on past experiences and “rule of thumb” estimations. The lack of formal methodology can be attributed to the large process gap between the network planners and the business analysts. From the network point of view, the network planners strive to improve network performance via fine tuning and optimizing upgrade decisions. Very little concern is given to the profitability of the resulting investments. From the business point of view, the business analysts have a very coarse understanding of how improved network performance

can lead to future revenue generation. Better network performance directly translates to more profit is a common assumption. Considering the intricate relations among network operations, customer behaviors, and market dynamics that jointly influence service profitability, such an assumption is overly naive. A general and comprehensive analytical model linking these three factors to service profitability is then extremely beneficial and timely. In surveying literatures, we find that very little is done in studying the causes of customer behavior and its effects on network service profitability. Research in network planning and upgrades often assumes direct and simple relationship between improved network performance and revenue. As the customers are the central source of revenue in the network service industry, they should be a key focus of analysis when investments in network infrastructures are made. Research in market science and economics presents many insightful observations and empirical studies on service utility, customer behavior, and profitability, but remains descriptive and incomplete. This lack of formalization prevents the integration of key customer and market factors in network planning and upgrade analysis and produces ineffective network upgrade decisions that do not reflect customer behaviors and service dynamics, and do not give good service profitability estimates.

In this paper, we establish an analytical modelling approach relating the performance delivered by a network service infrastructure to the satisfaction of its customers and consequently to the network service provider’s profit. We show that network upgrade and planning strategies should be made in accordance to their influences on customer satisfaction and the resulting changes in customer behavior. The ability of a service provider to retain and grow its customer population over time has an immediate impact on service revenue and is an invaluable indicator for network upgrade and planning operations. Based on a number of influential theories in economics and market science, we show that there is a strong ground for the derivation of well-behaved mathematical models linking the network service performance, the customer behavior and the market dynamics to profit. Based on this approach, we construct a generalized model, with meaningful parameters to reflect varieties of network service characteristics, customer attributes, and market conditions. Through analysis and simulation, we demonstrate how this model can capture SP service trends and customer behaviors, and its application to network upgrade decision processes. We find that the effectiveness of a network upgrade and planning strategy is highly dependent on the customers’ access behaviors, QoS sensitivities, service

expectations, past experiences, service competitiveness and market growth trends. For the service providers, ensuring that service quality meets customers' expectation is of paramount importance, and service differentiation may improve customer retention rate resulting in better revenue generation even without additional customer charges. The benefit of our approach is not restricted to network planning and upgrades, but is equally important to network demand forecasting, network service analysis, and others.

The rest of this paper is organized as follows: Section II presents a summary of current industry practices and academic research. Section III presents our modelling approach and its rationale, while Section IV details the construction of a forecasting model following our approach. Section V analyzes the forms of our perception function and the impact of model parameters, followed by case studies and simulations in Section VI. Section VII concludes with final remarks and future prospectives.

II. PROSPECTIVES AND LITERATURE WORKS

In conducting formal analysis of investment decisions, it is well understood that the soundness of a decision is dependent on the soundness of the analytical model and the value of the analyzed data. In the context of network services, we are presented with a rich reservoir of network information, ranging from statistical information gathered from Management Information Base [1] (e.g. via SNMP [2]) to active end-to-end measurements (e.g. ping). Advanced tools, such as Cisco NetFlow [3], are even capable of tracking individual traffic flows. Traditional customer management processes (e.g. customer relation management) gather vast amount of customer information in the form of customer surveys, service usage, trouble-ticket logs, etc.

For a network service provider, its customers, the sole source of revenue, are the crucial link between network performance and service profitability. Hence the willingness of the customers to repurchase services should be the focus of analysis. In the context of network service operations, the satisfaction of a customer is strongly influenced by the service performance he/she receives from the underlying network infrastructure. It is then apparent that correlating network performance and customer information in an analytical process can provide crucial guidance to the effect of network improvements on customer satisfaction, which ultimately influences the customer's intention to repurchase. A number of market studies on Telecom service operators world-wide have confirmed the existence of these relationships [4][5][6].

Some works in network research [7][8] have recognized the importance of analyzing both the customer profile and the network information in a business decision process. However, the means of correlating the two aspects are missing [7] and there is no method for mapping network performance to service utility [8]. Using real option pricing, d'Halluin

et al. [9] present a method for determining best investment time for link capacity upgrades. Their work evaluates profitability as a function of network usage, where customer dissatisfaction is modelled with a simple discount factor. Similarly, Jagannathan et al. [10] propose a revenue-based optimization for network upgrades. The profitability of a component is assessed based on the amount of customer traffic it supports, assuming previously unsatisfied customers are satisfied after upgrades. In these works, little effort is made in modelling the actual customer behaviors induced by their perceived service utilities, or on the subsequent shifting of consumer market dynamics. In our past work [11], we present a customer-centric framework for network upgrade optimization. The work projects network QoS performance onto customer satisfaction and then linearly maps to future revenue. Some attention is paid to market dynamics in terms of new market growth. Although the framework is sound, the relationships are overly simplistic to capture the complexities of customer behavior and market competitions.

In the area of network charging and pricing, service profit maximization is often the aim of investigation based on which various charging schemes are proposed and analyzed. Mitra et al. [12] consider pricing and routing as a joint optimization problem in multi-service networks where revenue maximization could be achieved by not only charging traffic based on usage but also routing traffic through low cost routes. Works on usage based charging, such as [13][14], conduct service charging based on the volume of customer traffic and access time. The pricing schemes may be variable such that a customer is charged based on fluctuating demand. Shakkottai and Srikant study the effect of multi-ISP competitions on service pricing [15]. Modelling the competitors as a non-cooperative game, they are able to draw insightful conclusions about the pricing strategy in both local and transit ISP markets. Pricing is an important factor of service profit because it maximizes the monetary benefit a service provider can draw from its customers. Our work investigates another important factor of profit: customer population. By studying the cause and effect of customer satisfaction, we bring focus and structure to some of the key factors influencing customer retention and growth.

Our work is also complementary to works on bandwidth provisioning and network dimensioning. The goal of bandwidth provisioning and network dimensioning research is to find the optimal resource allocation that maximizes network performance and profit. Our model can aid in this maximization process by providing the mathematical means to evaluate the various methods of resource allocation in terms of their impact on customer satisfaction and hence the resulting customer population. Our model is generic and applicable to provisioning problems in other network infrastructures as well. For example, Duan et. al. [16] consider the bandwidth provisioning and SLA assurance problem in Service Overlay Networks (SONs). Their analysis is conducted on customer flows with respect to specific QoS bounds. Our computation of QoS sensitive service utility

takes a similar approach. However, in our utility computation, we also consider network fluctuations as a cause of customer dissatisfaction. Their work evaluates revenue generation as a function of link traffic volume, access time and levels of QoS. They consider variable traffic demand in daily cycles similar to what we have constructed in our simulation setup. Rather than computing revenue directly from network performance and usage as in their work, our model evaluates the impact of service performance in terms of customer satisfaction which influences the customer's intention to repurchase the service. This could provide an alternative evaluator for their algorithm in determining the best bandwidth provisioning plan in SONS.

Customer relations and profitability have been the subject of significant research in the fields of market science and economics. The well known expectancy-disconfirmation theory [17][18] relates service utility to customer satisfaction, based on the classic adaptation theory from psychology. The work views expectation as an adapted reference point for the customers, upon which satisfaction is the result of customer value judgement on expectation and perception. Later finding [19] suggests strong relationships among satisfaction, perceived quality, and disconfirmation. Anderson and Sullivan [20] follow up on these works with a descriptive model relating service quality to customer repurchase intention. However, their work remains qualitative and does not address the issue of expectation adjustment and market dynamics. Bolton [21] proposes a dynamic model for the duration of provider-customer relationships in continuous services. Through an iterative expectation update process, the work formalizes the influence of customer satisfaction on customer retention and increased sales volume. The model is refined and tested over a 22-month period with cellular customers. The linkage between expectancy and customer retention is coarsely treated in this work and the impact of divergent service quality on customer experience is not considered. To obtain service utility, SERVQUAL [22][23][24] is the most-used and proven model in market science. It categorizes service utility into five aspects: tangibles, empathy, assurance, responsiveness and reliability. The model is focused primarily on service industries and relies on consumer survey based data collection. In a recent study [5], the SERVQUAL model has been shown to capture customer's quality perception of China's Telecommunication services. Also in this work, network quality is found to be an additional SERVQUAL aspect for network services.

With the vast amount of existing conceptual and empirical results from market science and economics, we believe there is a strong foundation for deriving an analytical forecasting model for network service operations. We propose a methodology for formalizing the relationships between network performance, customer satisfaction, and service profitability. The approach covers the computation of utility for network services, the derivation of customer satisfaction based on service utility, and the projection on service profitability from customer repurchase intentions and market dynamics. Following this approach, we construct a network service specific forecasting

model capable of forecasting service profitability induced by network infrastructure improvements. In the context of this paper, we make the following assumptions: the network service market is an open market with multiple competitors; The customer is rational in his/her purchase decisions and does not exit the service market; All competitors of the network service market charge similar price, have identical technology attractiveness from the customer's perspective and employ similar advertisement strategies; the pricing for the service is flat rate subscription based. The computation of our network utility functions is theoretical; It relies on end-to-end QoS measurements of the customers and knowing the access behavior (traffic flow and access time) and the QoS requirements of the customer. Our prior work [11] provides details into how such measurement could be conducted and computed in practice.

III. A MARKET SCIENCE METHODOLOGY

In this section, we show how network performance, customer satisfaction and service profitability are related in market science research, and present our modelling methodology. A key driver of our approach is the well-established expectancy-disconfirmation theory [17][18] which relates expectation, perceived quality and disconfirmation to customer satisfaction. The perceived quality refers to the service utility a customer obtains from service usage, while expectation represents the expected utility a customer formulates before using the service. Disconfirmation is then the discrepancy between the expectation and the perceived quality. Anderson and Sullivan [20] refined this theory in a customer satisfaction framework (Figure 1).

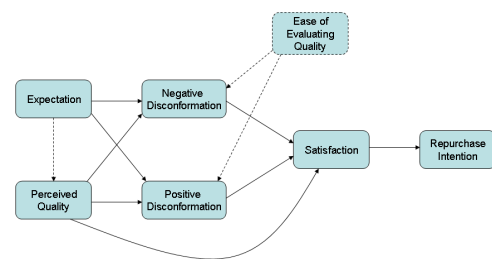


Fig. 1. Customer Satisfaction Model (Anderson and Sullivan)

They consider disconfirmation to have a positive and a negative component that are influenced by expectation and perceived quality. The customer satisfaction is then a function of perceived service quality and both components of disconfirmation. The perceived quality is affected by expectation based on the observation: when the difference between expectation and perceived quality is small, customer tends to equate perception to expectation. Furthermore, the level of disconfirmation is positively related to ease of evaluating quality. For network services, the ease of evaluating quality is high as service quality can be readily measured based on the network performance and the application requirements. Hence there is very little ambiguity in customer's perception of quality, and we simplify away this factor in our customer

satisfaction relationships. Furthermore, their claim that expectation influences perception is controversial as a number of important findings [21][25][26][27] supports the theory that perceived quality influences expectation via a dynamic update process. Based on these works, we reverse Anderson and Sullivan's expectation and perception relationship and formulate an expectation update process.

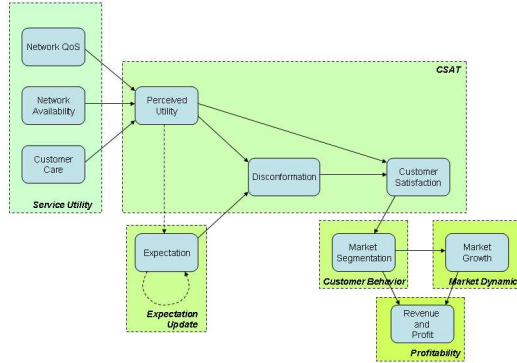


Fig. 2. Modelling Service Profitability

Figure 2 presents our modelling approach. Our view of the customer satisfaction model (CSAT) is a modified Anderson-Sullivan model. The expectation model updates a customer's future service expectation based on past expectations and current utility perception through a recurrent process in our expectation update model. The CSAT model takes as input the service utility, referred to as the "antecedent" of customer satisfaction [20]. It is computed through a utility model that operates on network performance and service attributes. Specialized from SERVQUAL model, we consider three aspects of network services: service quality, service availability and customer care. The "consequence" of customer satisfaction is customer's intention to repurchase [20]. It is captured in our customer behavior model, with regard to market competition and customer desire, to assess subscriber population change via a Bayesian decision process. The output of the customer behavior model is an estimation of the market segmentation: service provider retention, competitor retention, churn, and turnover from competitors. In our market dynamic model, the attractiveness of the service to new entry customers is projected using the Bass growth model [28]. The service profitability is then computed based on the revenue generating potential, derived from the market segments, and the service cost. Since network services are continuous where customers make periodic repurchase decisions (e.g. monthly for xDSL services), the entire process can be iterated through consecutive decision periods, providing long term profitability forecasts of network service operations.

We believe a forecasting model developed from this market science methodology provides significantly better assessment on the impact of network performance on network service profitability, compared with the simple linear models used in network planning research today. In the following section,

we detail the construction of such an analytical forecasting model following our methodology and show how it can capture important market trends and customer behavior in later sections.

IV. FORECASTING SERVICE PROFITABILITY

In this section, we detail the construction of our analytical model. We first introduce the computation of utility based on network service performance (Section IV-A) and then construct the customer satisfaction model (Section IV-B), followed by a formalization of the expectation update process (Section IV-C). Formulating the outcome as a decision problem, we estimate the market segmentation in customer behavior model (Section IV-D) and then deduce the growth of new entry customers in market dynamics model (Section IV-E). Finally, service profitability is computed as a function of revenue and cost (Section IV-F). Table I presents a list of the model parameters.

Parameter	Appears in	Definition
γ_1	Service utility	Customer preference for downstream throughput
γ_2	Service utility	Customer preference for upstream throughput
α_1	Service utility	Customer preference for service quality
α_2	Service utility	Customer preference for service availability
α_3	Service utility	Customer preference for customer care quality
μ_1	CSAT	Perception function concavity control
μ_2	CSAT	Perception function concavity control
μ_3	CSAT	Impact of negative disconfirmation (convexity)
ω_p	CSAT	Maximum value of perception function
ω_{dp}	CSAT	Maximum value of disconfirmation function
ω_{dn}	CSAT	Minimum value of disconfirmation function
κ_a	Expectation update	Assimilation factor
κ_r	Customer behavior	Resistance factor
β_G	Expectation update	Positive disconfirmation modifier
β_L	Expectation update	Negative disconfirmation modifier
β_M	Expectation update	Memory factor
m	Expectation update	Memory length
p	Market dynamic	Innovator factor
q	Market dynamic	Imitator factor
S	Market dynamic	Maximum market potential (i.e. saturation point)

TABLE I
LIST OF MODEL PARAMETERS

A. Service Utility and Perceived Utility

As noted by Dabholkar [29], customer satisfaction and utility are not the same construct. Satisfaction is a customer's subjective evaluation of the service performance, while utility is its objective measurable quantification. There are two concepts of utility presented in this section: service utility and perceived utility. Service utility denotes a set of service related performance metrics that are measurable or observable. Together, they yield a single quantitative evaluation of utility: the perceived utility. We first discuss service utility and its computation.

The SERVQUAL model [23] identified tangibles, empathy, assurance, responsiveness and reliability as the five major aspects of service quality. In the context of network services, tangibles, empathy, assurance and responsiveness can be grouped together under customer care, including helpdesk support, installation, troubleshooting, billing service, on-call technical support, etc. Reliability is readily mapped to network

service availability, often regarded as an essential factor in network service contract. Empirical studies done in Telecom services from Germany, US, and China [5][6] confirm the applicability of SERVQUAL to network services and suggest network quality as an additional aspect of SERVQUAL. In accordance, we consider service utility U as consisting of three basic aspects: service quality, service availability, and customer care. Service quality captures the network quality aspect by considering customer observed network QoS performance. Service availability represents the network availability experienced by the customer. The three service aspects are further documented by the TeleManagement Forum (TMF) in its SLA handbook suite [30].

To compute service quality Q , we consider factors related to network QoS of the customer's traffic flows, the application requirements, and the customer's own preferences. Let a *service path* denote an end-to-end network path carrying a customer's service traffic running a particular application. For a service path j of customer i , the service quality Q_{ij} is computed by considering a networked application to belong to one of two categories: QoS-sensitive services and QoS-insensitive services. QoS-sensitive services are applications whose satisfactory performance is contingent on fulfilling certain QoS requirements. For example, a multimedia stream has stringent minimum throughput and maximum round-trip delay bounds, while a web browsing session requirement is more tolerant. On the other hand, QoS-insensitive services are applications that do not have specific QoS requirements. FTP and P2P applications are good examples of this. Their performance is best computed based on an overall measurement of throughput quality.

For QoS-sensitive services, we model Q_{ij} based on the concept of *defective service instances* (DSI). We define a defective service instance experienced by a customer i on a service path j , denoted by D_{ij} , as a series of consecutive network QoS measurements whose values are below the QoS requirements of the supported application. We further observe that during the course of a network trouble, the QoS measurements may fluctuate wildly above and below the QoS requirements. Hence a network flux parameter is introduced to account for this fluctuation. We say that the first observed QoS measurement below the QoS requirements signals the onset of a D_{ij} instance, and ends when up to network flux number of consecutive QoS measurements are recorded as satisfying the QoS requirements. Let A_{ij} be the total access time of customer i on service path j , and $l(D_{ij})$ be the time length of D_{ij} , then Q_{ij} takes on the following form:

$$Q_{ij} = \frac{A_{ij} - \sum l(D_{ij})}{A_{ij}} \quad (1)$$

for QoS-sensitive services

For QoS-insensitive services, we model Q_{ij} based on the average throughput (P_{uij}^a for upload and P_{dij}^a for download) and the maximum bandwidth (P_{uij}^o and P_{dij}^o respectively). The maximum bandwidth is the capability limit of the customer's service offering (e.g. 2Mb/s customer download ceiling for

xDSL service). Let γ_1 and γ_2 represent the download and upload performance preferences of the customer, then Q_{ij} is computed as:

$$Q_{ij} = \gamma_1 \frac{P_{dij}^a}{P_{dij}^o} + \gamma_2 \frac{P_{uij}^a}{P_{uij}^o} \quad (2)$$

$\gamma_1 + \gamma_2 = 1$, for QoS-insensitive services

Given the above formulation of service utility. We can now define the computation of perceived utility. Let W_{ij} denote the percentage of time a service path j of customer i is deemed available, C_i be a scalar rating (between 0 and 1) of customer care service for customer i , SP_i be a set of service paths customer i uses, and α_1 , α_2 , and α_3 be customer i 's weight preferences for service quality, service availability, and customer care respectively, the perceived utility for customer i is expressed as:

$$U_i = \frac{\alpha_1 \sum_j (Q_{ij} \times A_{ij})}{\sum_j A_{ij}} + \frac{\alpha_2 \sum_j (W_{ij} \times A_{ij})}{\sum_j A_{ij}} + \alpha_3 C_i \quad (3)$$

where $j \in SP_i$ and $\alpha_1 + \alpha_2 + \alpha_3 = 1$

Taking as input the network and service performance of customer i 's service paths, Equations 1, 2 and 3 yield the perceived utility of customer i , normalized between 0 and 1. This is a unified quantification of the service utility according to customer's service preference and serve as the input to the perception and the disconformation functions, described in Section IV-B. We note that the presented utility model is theoretical. Work in [11] gives a pragmatic framework on how the above computations can be performed in practice. Furthermore, Section VI also provides some demonstration on how such computation could be carried out in regional networks.

B. Customer Satisfaction (CSAT)

Customer satisfaction can be modelled through the interaction between perceived utility and expectation [17][18], expressed as a linear combination of a perception function and a disconformation function. Let f_1 be the perception function, f_2 be the disconformation function, U_{pi} and U_{ei} be the perceived utility and expected utility (i.e. expectation) of customer i , then the general form of customer satisfaction Γ_i for a customer i is given in [20] as:

$$\Gamma_i = f_1(U_{pi}) + f_2(U_{pi} - U_{ei}) \quad (4)$$

The perception function gives the baseline customer satisfaction obtained from service utility, while the disconformation function modifies this satisfaction value based on the discrepancy between perceived utility and expectation (i.e. disconformation). The initial value of U_{ei} for new entry customers of a service can be computed using expected network service performance derived from service contract terms. This perception-disconformation theory for customer satisfaction has been confirmed in many empirical market research over the years, including very recent studies done in the Telecom sectors [4][5][6]. In the subsections below, we derive general mathematical forms for the perception and the disconformation functions.

1) *The perception function:* The perception function f_1 is a mapping between perceived utility and baseline customer satisfaction. It is described in [20] as an increasing concave function starting at the origin (i.e. $f_1(0) = 0$). Its general shape is conceived based on the observation that as the utility increases, the customer becomes less sensitive to changes in utility. We express the rate of change of the perception function as:

$$f_1''(x) = \mu_2 x - \mu_1 \quad (5)$$

where $x = U_{pi}$, and $\mu_1, \mu_2 \geq 0$

The parameters μ_1 and μ_2 control the concavity of the perception function. In Section V, we will discuss our choice of this particular form f_1'' . Integrating Equation 5 yields:

$$f_1'(x) = \int f_1''(x)dx = \frac{\mu_2}{2}x^2 - \mu_1 x + \Psi \quad (6)$$

where $x = U_{pi}$, and $\mu_1, \mu_2 \geq 0$

The constant Ψ is a weight that ensures $f_1'(x)$ remains positive (i.e. f_1 is an increasing function) for all possible values of x . The perception function then takes on the following form:

$$f_1(x) = \int f_1'(x)dx = \frac{\mu_2}{6}x^3 - \frac{\mu_1}{2}x^2 + \Psi x + C \quad (7)$$

where $x = U_{pi}$, and $\mu_1, \mu_2 \geq 0$

The constraint $f_1(0) = 0$ yields $C = 0$.

We observe that the domain of f_1 is bounded between 0 and 1. Moreover, we would like $f_1''(x)$ to be non-positive and $f_1'(x)$ to be non-negative for all possible values of x , and control the maximum value of f_1 via parameter ω_p (i.e. $f_1(1) = \omega_p$). We thus have the following set of constraints on parameters of f_1 :

$$\begin{cases} \mu_1 \geq \mu_2 & \text{from } f_1''(x) \leq 0 \\ \Psi \geq \mu_1 - \frac{\mu_2}{2} & \text{from } f_1'(x) \geq 0 \\ \Psi = \frac{\mu_1}{2} - \frac{\mu_2}{6} + \omega_p & \text{from } f_1(1) = \omega_p \\ \mu_1, \mu_2 \geq 0, \omega_p > 0 \end{cases} \quad (8)$$

Satisfying the constraint set of 8 entails solving the following inequality:

$$\frac{\mu_1}{2} - \frac{\mu_2}{6} + \omega_p \geq \mu_1 - \frac{\mu_2}{2} \quad (9)$$

where $\mu_1 \geq \mu_2$ and $\mu_1, \mu_2 \geq 0, \omega_p > 0$

By solving Inequality 9, we can express the constraint on μ_1 as:

$$0 \leq \mu_1 \leq 2\omega_p + \frac{2}{3}\mu_2 \quad (10)$$

The constraint of 10 suggests that the upper bound of μ_1 is positively related to the upper bound of μ_2 . As we would like the concavity parameter μ_1 to have the largest possible value range, and given the constraint $\mu_1 \geq \mu_2$, then we obtain the maximum value range of μ_1 when $\mu_1 = \mu_2$. This leads to a desirable simplification of f_1 . Figure 3 demonstrates the general characteristics of the perception function. In summary, f_1 is a function of perceived utility, with the following form:

$$f_1(x) = \frac{\mu_1}{6}x^3 - \frac{\mu_1}{2}x^2 + \left(\frac{\mu_1}{3} + \omega_p\right)x \quad (11)$$

where $\mu_1 \leq 6\omega_p, \mu_1 \geq 0$, and $\omega_p > 0$

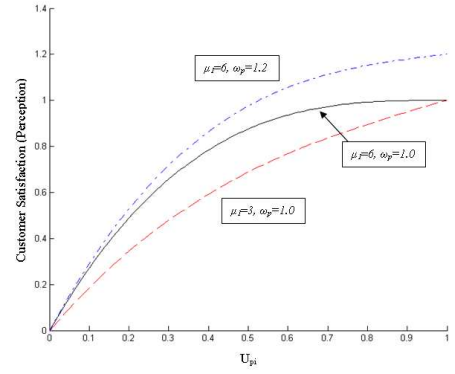


Fig. 3. The Perception Function

2) *The disconformation function:* The disconformation function f_2 accounts for the subjectivity of customer evaluation given a reference point (i.e. expectation). Tversky and Kahneman [31] found that “losses relative to a reference value looms larger than gains”. Grounded on this psychological theory, Anderson and Sullivan [20] suggest that customer satisfaction is mildly increasing when perceived utility exceeds expectation and is significantly reduced when perceived utility falls below expectation. We formalize this interaction as a two-piece increasing function:

$$f_2(x) = \begin{cases} \omega_{dp}x & x \geq 0 \\ \omega_{dn}(x+1)^{\mu_3} - \omega_{dn} & x \leq 0 \end{cases} \quad (12)$$

where $x = U_{pi} - UTIL_{ei}$, $\mu_3 \geq 0$, and $\omega_{dp}, \omega_{dn} > 0$

We observe that the domain of f_2 is bounded between -1 and 1. The function is continuous (i.e. the two piece-wise functions converge at $x = 0$). The parameter ω_{dp} controls the maximum value of f_2 (i.e. maximum positive disconformation) while ω_{dn} controls the minimum value of f_2 (i.e. maximum negative disconformation). μ_3 regulates the impact of negative disconformation on customer satisfaction. The general characteristics of the disconformation function is illustrated in Figure 4.

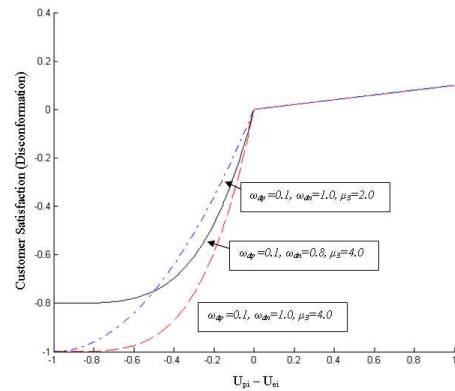


Fig. 4. The Disconformation Function

3) *Customer satisfaction*: From Equation 4, 11 and 12, we observe that Γ_i is bounded between $-\omega_{dn}$ and $\omega_p + \omega_{dp}$. In general, the choice of ω parameters should follow: $\omega_p \geq \omega_{dn} > \omega_{dp}$. ω should be fixed for all customers of a service and ω_{dp} should be small compared to ω_p .

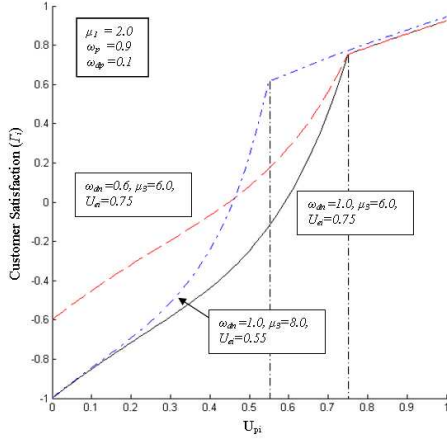


Fig. 5. The Customer Satisfaction Function

As we observe in Figure 5, the rate of change in customer satisfaction differs significantly when perceived utility falls below and exceeds expectation. The rate and severity of dissatisfaction (controlled by ω_{dn} and μ_3 respectively) reflect different customer's tolerance to negative disconfirmation. Our formalization of the customer satisfaction fits a rational customer's subjective evaluation of the service utility, and conforms to empirical findings [17][18][20][31]. In addition, we offer a set of well-defined control parameters to fit different service characteristics, and individual customer's preferences and sensitivities.

C. Expectation Update

Empirical studies [27][32] suggest that a customer adjusts his/her future expectation of service utility based on current expectation and perception. The studies also find favorable disconfirmation increases future expectation while unfavorable disconfirmation has the opposite effect.

Through an expectation update process, we deduce a customer's future expectation as a function of the customer's current expectation and disconfirmation, subject to two psychological factors: assimilation and experience. When the relative level of disconfirmation is small, a customer tends to equate the perceived utility to the expected utility, due to assimilation effect [21]. Furthermore, as a customer perceives consistent service utility over time, he/she gains experience with the service, and consequently is less sensitive to short term utility fluctuations [27]. In other words, the customer gradually establishes long term reputation of the service.

Let κ_a be the assimilation factor, a customer i 's future expectation U_{ei}^* has the following form:

$$U_{ei}^* = \begin{cases} U_{ei} & \left| \frac{U_{pi} - U_{ei}}{U_{ei}} \right| \leq \kappa_a \\ h(U_{ei})[U_{pi} - U_{ei}] + U_{ei} & \text{otherwise} \end{cases} \quad (13)$$

U_{ei}^* is constrained to $0 \leq U_{ei}^* \leq 1$

The parameter κ_a is constrained ($0 \leq \kappa_a \leq 1$) and should be a very small value (e.g. 0.01). The function $h(U_{ei})$ adjusts the expectation as a factor of the disconfirmation. Our general form of Equation 13 is established based on assimilation theory of economics [26], where new information are assimilated as an aggregate quantity over time. According to literatures, Equation 13 should exhibit three characteristics. First, given the same expectation, a negative disconfirmation is weighed much more heavily than a positive disconfirmation [31]. This effect is similarly reflected in the construct of disconfirmation function. Second, a positive disconfirmation has a greater impact on U_{ei}^* as U_{ei} decreases, and conversely a negative disconfirmation has a greater impact on U_{ei}^* as U_{ei} increases [21]. Third, the longer a customer experiences consistent utility, the less impact on expectation should a short term utility fluctuation have [27]. Based on these characteristics, we construct $h(U_{ei})$ as such:

$$h(U_{ei}) = \begin{cases} \beta_G \beta_M^m (1 - U_{ei}) & \frac{U_{pi} - U_{ei}}{U_{ei}} > \kappa_a \\ \beta_L \beta_M^m U_{ei} & \frac{U_{pi} - U_{ei}}{U_{ei}} < -\kappa_a \end{cases} \quad (14)$$

where $0 \leq m \leq \Upsilon$, $0 \leq \beta_M \leq 1$, and $1 \leq \beta_G < \beta_L$

β_G and β_L are the positive and negative disconfirmation factors respectively. β_M is the memory factor and m the memory length. The term β_M^m controls the significance of the new information (i.e. current disconfirmation) on the aggregate (i.e. expectation). As m increases, β_M^m decreases. We use integer values for m , representing the number of repurchase evaluations the customer underwent while using the service. The constant Υ represents the maximum memory length a customer keeps track of. The value of m is updated (m^*) based on the following equation:

$$m^* = \begin{cases} m + 1 & \left| \frac{U_{pi} - U_{ei}}{U_{ei}} \right| \leq \kappa_a \\ m - 1 & \text{otherwise} \end{cases} \quad (15)$$

m^* is constrained to $0 \leq m^* \leq \Upsilon$

The initial value of m is set to 0. We infer from Equation 15 that as customer regularly experiences consistent service performance, he/she is more insulated from short term performance fluctuations. Conversely, when performance significantly fluctuates over time, the customer is unable to make an experienced evaluation of the service, and hence his/her reliance on new information does not diminish with time (i.e. the divergence effect).

In this section, we formally constructed the process of expectation update, with consideration for assimilation and experience effects. The value of expectation is bounded between 0 and 1, and is adjusted based on perceived utilities in an iterative fashion.

D. Customer Behavior: Repurchase Decision and Market Segmentation

Repurchase intention is the direct consequence of customer satisfaction [20]. Researches in inter-temporal planning (e.g. [25]) state that customers re-estimate purchase decisions periodically based on previous estimates and new information. Furthermore, there exists a strong linkage among customer satisfaction, future expectation, and repurchase intention [20][21]. We formulate the customer's repurchase intention as a decision problem, subject to the following assumptions: we assume the customer is rational in his/her purchase choice and does not exit the service market (i.e. the customer seeks maximization of future satisfaction); we further assume all competitors in the same service market charge similar price, have identical technology attractiveness from the customer perspective, and employ similar advertisement strategies. Although the above factors could be included in our analysis, we discount them for sake of simplicity. In practice, with the fierce competitions exist among SPs, these assumptions often hold. The customer's decision to use a service from a particular service provider is primarily influenced by the customer's current level of satisfaction and expected future utility. The finding of [32] suggests that when a customer chose a service brand that meets his/her desire, he/she is likely to choose the same service brand again regardless if the brand has the highest expected performance in the market or not. Therefore, we consider a customer i will stay with a service provider if his/her customer satisfaction at the end of the current service period is above such a desire threshold Γ_i^D . If below Γ_i^D , the action of choosing a new service provider is a decision problem in which the customer attempts to maximize his/her future satisfaction based on his/her future expectations of similar services. Let U_{ev} be the future expectation of service v estimated by a customer i , let k be the service customer i has just used, let Φ be the set of all similar services, and let κ_r be the resistance factor of customer i , then we can express the decision problem as:

$$\max \{f_1(U_{eik}) + \kappa_r, f_1(U_{ev})\} \quad (16)$$

$$\forall (v \in \Phi, v \neq k)$$

The parameter κ_r is a small satisfaction modifier representing the extra effort (e.g. service switching time, etc.) customer i has to spend in order to switch service provider. Equation 16 relies on precise knowledge of a customer's future expectations. In practice, a customer's expectation of services he/she has not used can at best be estimated from service reputation with some uncertainty. Hence, we reformulate Equation 16 as a Bayesian decision problem [33]. Let $F_{ev}(\mu_{ev}, \sigma_{ev})$ be the probability distribution of expectation of service v , with mean μ_{ev} and standard deviation σ_{ev} , our decision problem can be expressed as:

$$\max \left\{ f_1(U_{eik}) + \kappa_r, \int f_1(\mu_{ev}) dF_{ev}(\mu_{ev}, \sigma_{ev}) \right\} \quad (17)$$

$$\forall (v \in \Phi, v \neq k)$$

In Equation 17, $f_1(\mu_{ev})$ is the loss function and $F_{ev}(\mu_{ev}, \sigma_{ev})$ is the prior distribution. Given overall customer turnover rate in the market, Equation 17 could also be used in a random

sampling process to forecast service switching decisions of customers from other competitors. Ultimately, applying this decision process to all consumers in the market classifies the consumer population into three disjoint partitions: the set of customers with intention to repurchase the same service k (Ω_R), the set of customers choosing not to use service k (Ω_N), and the set of customers switching to service k from another service provider (Ω_P).

E. Market Dynamic

Up to this point, we have considered the partitioning of the existing consumer market. The entry of new consumers in the market could be described by the Bass growth model [28]. This model is applicable to network service industry, as suggested by the techno-economic studies on European xDSL market penetration [34]. The Bass model categorizes new consumers that enter the market into two categories: innovators and imitators. The innovators enter the market without any incentives and they are the main consumer faction during the inception of the market; the imitators are attracted to the market by the innovators and they are the main consumer faction as the market matures. The hazard function of the Bass model, describing the conditional probability of new consumers entering the market, is formally expressed [28] as:

$$\frac{f(T)}{1 - F(T)} = p + qF(T) \quad (18)$$

where $0 < p < q < 1$ and $p + q = 1$

$f(T)$ is the probability density function over time T , while $F(T)$ is the cumulative function over T . The parameter p is the coefficient of innovators and q is the coefficient of imitators. In general, p is much smaller than q . Rewriting and integrating Equation 18 yield:

$$\int \frac{dF}{p + (q - p)F - qF^2} = \int dT \quad (19)$$

The solution to Equation 19 yields the cumulative function $F(T)$ [28]:

$$F(T) = \frac{1 - e^{-(p+q)T}}{1 + \frac{q}{p}e^{-(p+q)T}} \quad (20)$$

and the density function $f(T)$ [28]:

$$f(T) = \frac{\frac{(p+q)^2}{p} e^{-(p+q)T}}{\left(1 + \frac{q}{p}e^{-(p+q)T}\right)^2} \quad (21)$$

Figure 6 illustrates the characteristics of $f(T)$. The values of $f(T)$ when $T < 0$ has no practical meaning since $T = 0$ indicates the inception of the market. For ease of comparison, the p and q parameters in Figure 6 do not conform to the constraint $p + q = 1$. We observe that p specifies the initial consumer population size (i.e. $f(0) = p$), and q affects the arrival probabilities of the imitators.

Let S be the market potential (i.e. the maximum number of consumers), and $L(t)$ be the mapping function that maps real time t to time domain T of the Bass model, then we can represent the number of entry customers that choose service k as:

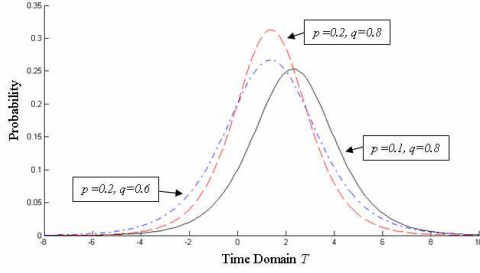


Fig. 6. Probability Density Function of Bass

$$\Omega_N = \frac{\Omega_R + \Omega_P}{\Omega_R + \Omega_P + \Omega_N} S[F(L(t_{c+1})) - F(L(t_c))] \quad (22)$$

The time value t_c denotes the end of current service period (i.e. current evaluation time), while t_{c+1} denotes the time of next evaluation. The last term in Equation 22 is the cumulative probability of new consumers entering the market from current time to next evaluation time. We estimate that a fraction of them will choose service k based on the competitiveness of service k at current time. This is represented by the first term of Equation 22.

In the above discussion, we have considered a single service market. For SPs that has multiple service offerings, a market dynamic should be established per service. We will show an example of this in Section VI.

F. Service Profitability

From our forecast of consumer market segmentations at time t_c , the revenue generating potential R_k of service k in $[t_c, t_{c+1}]$ time interval is:

$$R_k = \frac{(\Omega_N + \Omega_P) \times \xi_N}{\Omega_R + \Omega_P + \Omega_N} \quad (23)$$

The parameters ξ represent the price of service k to new customers ξ_N and old customers ξ_R in time interval $[t_c, t_{c+1}]$. Follow from Equation 23, the profitability of service k is then:

$$PROF_k = R_k - COST_k - PEN_k \quad (24)$$

The parameters $COST_k$ and PEN_k are the cost of running service k and the estimated monetary penalties (e.g. due to contract violation, etc.) from time t_c to time t_{c+1} .

V. MODEL ANALYSIS

In Section IV-B, we have formalized the customer satisfaction function based on a number of literatures. In the context of network services, we now discuss our particular choice of the perception function and analyze the impact of the parameters in the model.

A. Choice of the Perception Function

In constructing the perception function, we also considered two other simple equation forms (Equations 25 and 26). Both of them are concave increasing functions in the domain of 0 to 1.

$$f_1(x) = \omega_p x^{\mu_1} \quad (25)$$

where $0 \leq \mu_1 \leq 1$, $\omega_p \geq 0$, and $0 \leq x \leq 1$

or

$$f_1(x) = 1 - e^{-\mu_1 x} + (e^{-\mu_1} - 1 + \omega_p)x \quad (26)$$

where $\mu_1, \omega_p \geq 0$, and $0 \leq x \leq 1$

Similar to Equation 11, the μ_1 parameter controls the concavity and $f_1(1) = \omega_p$. Figure 7 illustrates the characteristics of Equations 11, 25 and 26.

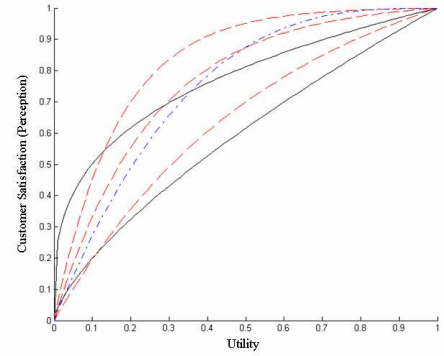


Fig. 7. Forms of Perception Functions

The solid curves are the forms of Equation 25 with varied concavities. These forms are useful in modelling services that have high customer satisfaction even when utility is low, and the effect of desensitization is not significant when utility is high. The dot slash curve is the perception function of Equation 11 with maximum concavity. The dash curves are the forms of Equation 26 with varied concavities. Unlike Equation 11, the forms of Equation 26 do not place constraint on μ_1 . However, for curves with similar concavity, the forms generated by Equation 11 delay the severity of desensitization until higher utility level. In our work, Equation 11 is chosen because it appears to fit what we can expect from network services best: the increase in customer satisfaction will be approximately linear to increase in utility when utility level is low and the effect of desensitization does not become very significant until utility level is high (i.e. over 0.7). In addition, the concavity factor of Equation 11 is more meaningful to analysis (i.e. f'' is in linear form). Higher orders of polynomials are also considered, but they do not add significant control to concavity. In practice, the choice of a best form should be network service specific and be determined based on empirical data gathered for the analyzed service.

B. Impact of The Perception and Disconformation parameters

The parameters ω_p , ω_{dp} and ω_{dn} define the range of customer satisfaction values. The maximum disconformation parameter ω_{dp} should be much smaller than the maximum perception parameter ω_p as utility above expectation does not induce significant satisfaction improvement from customers. The combination of ω_p and ω_{dp} gives the maximum ceiling value of customer satisfaction Γ . A value above 1 is not meaningful as Γ is bounded between 0 and 1. However, a value of below 1 is quite feasible, as Γ may be influenced by non-service related factors (e.g. a chronic complainer is unlikely to be fully satisfiable regardless of delivered service utility). The ω_{dn} controls the maximum impact a negative disconformation has on perception. When ω_{dn} is large, the degree of negative disconformation is also large. As Γ is non-negative, ω_{dn} should be at most as large as ω_p .

When the service utility is fixed, the parameter μ_1 of the perception function is linearly related to customer satisfaction. A higher μ_1 value results in a higher customer satisfaction value. Figure 8 illustrates the interactions among μ_1 , utility, and customer satisfaction.

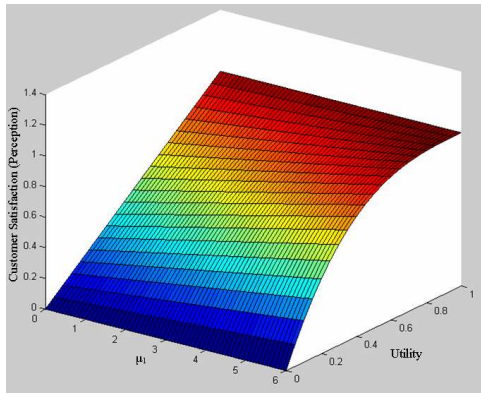


Fig. 8. Effect of μ_1 on Perception

Figure 8 suggests that customer satisfaction is particularly sensitive to the choice of μ_1 when the utility value is moderate (i.e. 0.4 ~ 0.8). For instance, given a utility value of 0.6, the customer satisfaction is as low as 0.6 when $\mu_1 = 0$, and as high as 0.95 when $\mu_1 = 6$. With high μ_1 values (i.e. $\mu_1 \geq 3$), the customer satisfaction increases much more rapidly when utility is below 0.5. We can infer from Figure 8 that when μ_1 is high (i.e. $\mu_1 \geq 3$), it is more beneficial for the network service provider to keep service utility at a moderate range (i.e. $U \approx 0.8$). However, this inference holds only if the effect of disconformation is low (i.e. the customer expectation is met or the customer has high tolerance to negative disconformation).

When perceived quality falls below expectation, the impact of negative disconformation on customer satisfaction could be significant. Parameter μ_3 controls the rate of this reduction. When utility is fixed, an increase in μ_3 exponentially decreases

customer satisfaction (Figure 9). However when negative disconformation is very low (i.e. below 0.1), increases in μ_3 approximately result in a linear reduction of customer satisfaction. We can thus infer that network service providers should always ensure that the perceived utility of a customer does not fall below his/her expectation.

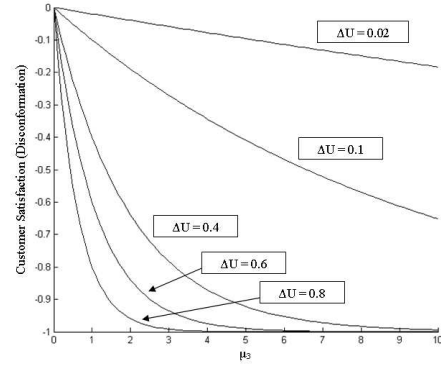


Fig. 9. Effect of μ_3 on Disconformation

In summary, for network services, where both μ_1 and the customer expectation are high (i.e. $\mu_1 \geq 3$ and $U_{ei} \geq 0.7$), customer satisfaction does not differ significantly when perceived utility exceeds expectation. However, when expectation is not met, negative disconformation will have a significant impact on customer satisfaction, depending on the value of μ_3 . Hence, to retain customers, it is sufficient for a network service provider to deliver service at a quality level matching the expectations of the customers, without maximizing their perceived utilities. However, this observation holds only if the customer does not have a low expectation of the service. Low service expectation yields overall customer satisfactions below the desire threshold Γ_i^D and drives customers to evaluate alternatives. We suggest the parameters of Γ to be acquired through data fitting techniques. The network performance of customers could be obtained in conjunction with customer satisfaction surveys overtime. The computed service utility should be plotted against customer satisfaction and then use best-fit techniques to determine the most appropriate function parameters.

C. Impact of other model parameters

Service utility parameters for QoS-insensitive services influence a customer's preference proportioning between upstream throughput performance γ_1 and downstream throughput performance γ_2 . This proportioning is very application and user dependent. For P2P applications, we typically expect γ_2 to be much higher than γ_1 , whereas for FTP-based applications, the proportioning depends on customer's access behavior. For customer preference parameters α_1 , α_2 and α_3 , the proportioning fundamentally influences the degree of impact each aspects of service utility has on the overall customer satisfaction, and therefore service

profitability. For example, when customer care preference α_3 is high, enhancing network infrastructure does not constitute good investment strategy. Hence it is important for a forecasting model to identify such customers as they influence the profit margin of network upgrades. All of the service utility parameters should be acquired via structured SERVQUAL customer survey. Survey methods used in Telecom customer satisfaction studies [5][6] could serve as guides.

In the expectation update process, the assimilation factor κ_a controls the likelihood of the assimilation effect. The perception of difference does not differ significantly between humans and should be small [26] (e.g. $\kappa_a = 0.01$). The parameters β_G and β_L are modifiers of disconfirmation. If we consider $U_{ei} = 0.5$, the impact of disconfirmation on expectation is differentiated by β_G and β_L . The value of β_G and β_L should be equal to or greater than 1, with β_L larger than β_G . The parameter β_M considers the effect of past experience. A larger β_M causes current disconfirmation to be evaluated more significantly on expectation with regard to experience, and the dissipation of this impact is slower as experience accumulates. More specifically, a customer without prior experience is not influenced by β_M (i.e. β_M^0). The cumulation of experience (i.e. $m \geq 1$) rapidly lessens the impact of current disconfirmation on expectation, represented by β_M^m . We further notice that experience is accumulated with consistent performance, whether good or bad, and can be destroyed by inconsistency.

The Bass model parameters p , q and S governs the general market growth pattern in a service market. The parameter values are determined via techno-economic studies (e.g. [34]) or growth analysis of similar service markets in the past.

VI. CASE STUDIES AND SIMULATION

In this section, we demonstrate the effectiveness and practicality of our approach through two sets of case studies and simulations. First, we show how our models could help in a network upgrade decision process and illustrate how key economic, customer and market factors that influence network service planning are captured in our models. Then we analyze the performance of a typical regional ISP network through simulation and show that by representative flow tracking, our model can be applied to WANs. A comparative analysis of the network infrastructure is conducted from three different perspectives: network utilization, customer traffic flow, and customer satisfaction.

As the basis of our first discussion, we simulate a network infrastructure and customer population that is representative of a real world network planning scenario, onto which we offer three equally promising upgrade strategies. We show that a sound upgrade decision could not be made by only considering network performance, even with the ability to track customer's access behaviors. We then present a step by

step application of our model incorporating the customer and economic factors and show that service profitability derived from customer satisfaction could be an effective decision indicator for network planning and upgrades. We further demonstrates how our expectation model captures the effect and durability of customer loyalty over long term and how different market dynamics play a crucial role in network service planning. Through this discussion, we also show how the model formally relate and explain some important market observations on customer behaviors and growth.

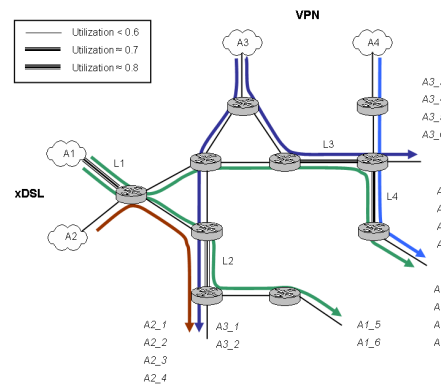


Fig. 10. Simulation Topology

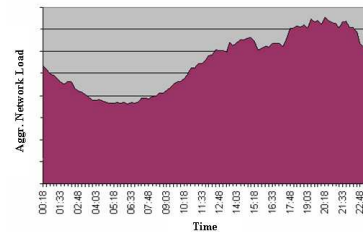


Fig. 11. Daily Aggregate Load of A Regional ISP Network

The network infrastructure as depicted in Figure 10 is realized in NS2 [35]. The link capacity is set to 24 Mbps. Two regions of xDSL customers (A1 and A2) and two regions of VPN customers (A3 and A4) generate a total of 20 service paths (e.g. A1_1, A2_1, etc.). Each service path is used by 5 customers with similar application characteristics, QoS requirements, and access time (Table II). However, each customer varies in performance preferences and service expectations. The routing in this setup is static, such that all customer flows will follow the pre-established paths. As the customers in regions A1 and A2 represents xDSL customers. We have chosen the traffic mix to be primarily a mix of web based light traffic (web browsing, email, etc.) and regular data transfer occurring in prime time after work. We also disperse sources of semi-permanent and permanent FTP traffic to represent P2P and other constant data transfer traffic often present in the SP networks. For the VPN customers, CBR traffics are used to represent their constant resource demand. For realism, the simulated network infrastructure

Path ID	Traffic Type	Requirements / Opt. BW	Start Time	End Time
A1_1	FTP	800 Kb/s Max.	18:00	23:00
A1_2	FTP	800 Kb/s Max.	16:00	23:00
A1_3	FTP	800 Kb/s Max.	6:00	24:00
A1_4	FTP	800 Kb/s Max.	0:00	24:00
A1_5	HTTP	120Kb/s, 100ms	18:00	23:00
A1_6	HTTP	120Kb/s, 100ms	16:00	23:00
A2_1	HTTP	120Kb/s, 100ms	16:00	23:00
A2_2	HTTP	120Kb/s, 100ms	18:00	23:00
A2_3	FTP	800 Kb/s Max.	6:00	24:00
A2_4	FTP	800 Kb/s Max.	0:00	24:00
A3_1	CBR	450Kb/s, 100ms	6:00	24:00
A3_2	CBR	450Kb/s, 100ms	0:00	24:00
A3_3	CBR	450Kb/s, 100ms	9:00	17:00
A3_4	CBR	450Kb/s, 100ms	11:00	19:00
A3_5	CBR	450Kb/s, 100ms	6:00	24:00
A3_6	CBR	450Kb/s, 100ms	0:00	24:00
A4_1	CBR	450Kb/s, 100ms	9:00	17:00
A4_2	CBR	450Kb/s, 100ms	11:00	19:00
A4_3	CBR	450Kb/s, 100ms	6:00	24:00
A4_4	CBR	450Kb/s, 100ms	0:00	24:00

TABLE II
CUSTOMER SERVICE PATHS

and customer behaviors are designed to facilitate traffic intermixing among customers of different service classes and introduce a varied mix of customer access behaviors. Additional background aggregate traffics modelled as Pareto flows establish a daily cyclic pattern (Figure 11). These aggregate traffic are introduced to obtain the desired average link utilizations (Figure 10), yet still reflect the typical daily network load observed by a SP. Details on the setup of aggregate traffics are presented in the latter simulation case. In our experiments, the 24 hr. daily cycle is mapped to 120 min. simulation time so that each simulation run is within reasonable time bound. With this setup being the network conditions and customer population at the deployment time of the network upgrades, we consider four upgrade options: no upgrade (base case), upgrade links L1 and L2 to 48 Mbps (option 1), upgrade links L2 and L3 to 48 Mbps (option 2), and upgrade links L2 and L4 to 48 Mbps (option 3). All three upgrade options have the same cost. Option 1 is an aggressive upgrade strategy aimed at pleasing xDSL customers, while option 2 and 3 are more balanced strategies. Each of the upgrade option is simulated multiple times in NS2 through a 24 hr. day (i.e. 120 min. simulation time) and the QoS measurements (i.e. delay and throughput) are taken at 1 min. intervals. The average measurements of each interval across runs are used to compute network performance for the customers.

When taking into account the customer access behaviors (i.e. customers' service path and service time), we could compute the perceived utility of each upgrade option. For simplicity, we assume the customers only care about service quality (i.e. $\alpha_1=1$, $\alpha_2, \alpha_3=0$). It then implies that the perceived utility is analogous to the ratio of average throughput to optimum bandwidth for FTP traffic, and to the percentage of non-defective service time for the other traffic. The solid lines in Figure 12 present the perceived utility of the customers under each upgrade option. In each region, the customers are

ordered on the graphs by their path IDs. In the base case of no upgrades, we notice that xDSL customers accessing path A1_3 and A1_4 have significantly better perceived utilities compared to other xDSL customers because they do not access link L1 and are not "prime time" traffic. Option 1 significantly increases the service performance of the xDSL customers at the expense of some moderate performance drop from the VPN customers, which seems quite acceptable. The perceived utility of some customers from region A1 remains low due to L3 link load. Option 2 and 3 are roughly equivalent as they improve the service performance of region A1_3 and A1_4 respectively. Although informative from a network performance point of view, this analysis provides few insight into which upgrade option is in fact the most beneficial, as all of the options improve performance for some customers. Without considering the economic and customer factors, there is little else that could be done. We now carry the computation of these options through the rest of our model.

For this scenario, let the expectation of the customers be normal distributions with means of 0.65, 0.7, 0.8 and 0.9 respectively for A1, A2, A3 and A4, and a standard deviation of 0.05. This distribution is used to reflect the diversity in customer expectations and the relative differentiation between the xDSL customers and the VPN customers. Figure 12 illustrates the perceived utilities, expectations, and customer satisfactions of the customers under each upgrade option. The choice of customer satisfaction parameters are taken so that the customer satisfaction function exhibits its general form as observed in empirical studies. In the base case, the xDSL customers have significant negative disconformations and consequently low satisfactions. Option 1 significantly improves the satisfactions of xDSL customers, although some of the customers from region A1 are still dissatisfied due to L3 link load. Interestingly, the additional influx of A1 traffics on L3 and L4 reduced the perceived utilities of VPN customers, just enough to make their perceived utilities to fall below expectations. Therefore, our computations of Γ indicate option 1 may not be a good upgrade option. Regarding option 2 and option 3, our model suggests that negative disconformations are eliminated in region A3 and A4 respectively in each option. When factoring in the Γ^D level, we further observe that option 2 seems to generate more dissatisfied customers than option 3 due to the high expectation rating in region A4. To accentuate our case, we consider a saturated xDSL and VPN market where our network service provider does not offer the best service. This market condition could be represented in our model with zero market growth and a 0.0 market turnover rate (from other competitors). According to our market segmentation model, this implies that more customers will leave the provider in option 2 compared with option 3. By determining the number of customers remaining with the service after each upgrade option, we could compute the retention rate and project the future profitability from our model as presented in Figure 13. With the cost of upgrades being equal, the outcome of our analytical model indicates option 3 is the more profitable option as long as the service charge for VPN is higher than

the service charge for xDSL. By following our model and factor in the customer's expectations, satisfaction conditions and market dynamics, we are able to arrive at a much more informed upgrade decision using service profitability as an indicator.

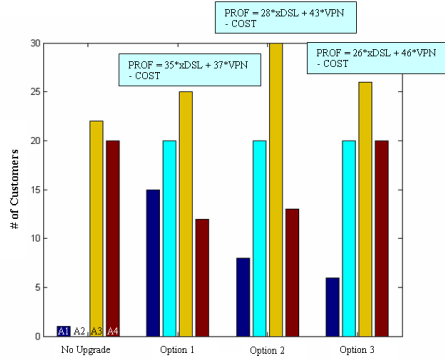


Fig. 13. Customer Retention of Different Upgrade Options

A commonly observed principle in market science states that service profitability is maximized with respect to customer's satisfiability. Rather than satisfy each customer, a business should strive to satisfy each satisfiable customer, and only if it is profitable to do so [36]. This phenomenon is manifested in our model, as illustrated in Figure 14. The top graph shows the computation of Γ for upgrade option 2, while the bottom graph shows the same computation except with raised ω_p value for the VPN customers. It suggests that if the VPN customers are difficult to satisfy (i.e. $\omega_p = 0.75$), then an upgrade option maybe ineffective despite improved service utility.

The long term interactions among service performance, customer experience and future expectation is a well studied topic in market science and economic psychology. Our model effectively captures many of their key observations. Consider a customer who has stayed with the service provider for 20 evaluation periods and has experienced consistent service performance, we subject the customer to low and inconsistent service performance for the next 50 evaluation periods and trace his/her service expectations (Figure 15) obtained from our expectation update process. The parameters β_L and β_G are general values taken based on our discussion in Section V-C, and κ_a is set to 0 (i.e. no assimilation) for simplicity. As shown in Figure 15a, in the short term (first 7 iterations), the customer's future expectations are not significantly influenced by perceived utilities as the customer has experience with consistent service delivery in the past. However, the customer gradually loses confidence with the service (iterations 8 to 17) and expectations become heavily dependent on short term perceived utilities. This trend confirms with the observations on expectation and customer experience [37][38]. When a customer is dissatisfied due to poor service performance in the short term, an experienced customer (whose future expectation is not significantly reduced) is more likely to

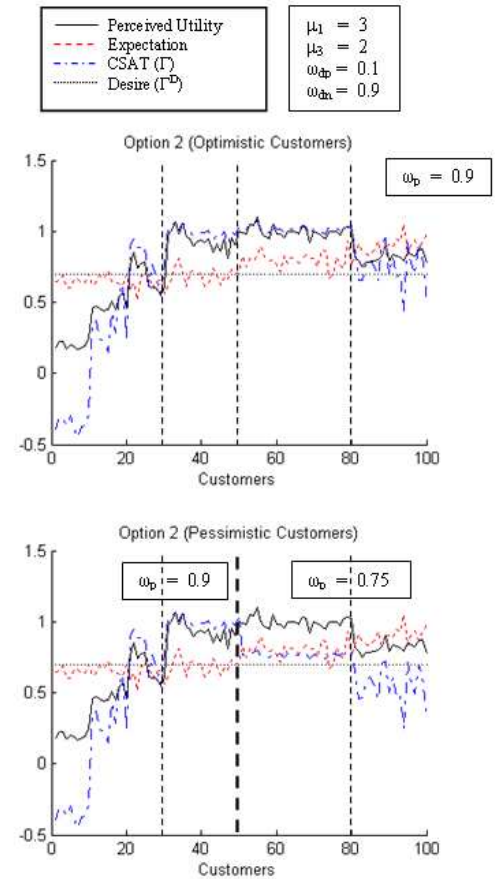


Fig. 14. Effect of Varied ω_p

be loyal than an inexperienced customer. The works on expectation further suggest that when customer perceives disconfirmation, the degree of adjustment to expectation is determined by the uniqueness of the event and the strength of previous expectation. In the first few iterations of our illustrated case (Figure 15a), the impact of disconfirmation on expectation adjustment is low. As the occurrence of disconfirmation increases, its impact is significantly more severe. The parameter β_M controls the weight of current disconfirmation on expectation. A higher β_M indicates a lower strength of the past expectation. In Figure 15b where β_M is higher, the impact of disconfirmation on expectation is significantly more severe even in the presence of long past experience. It is apparent that the interaction among expectation, performance, and customer satisfaction is a significant factor influencing the service profitability of SP operations and should be considered in the network upgrade decision process. The trends captured by our model integrate such factors in the network upgrade decision process.

Finally, we examine how varying market conditions can affect service profitability as presented in our model. Regarding the aforementioned three upgrade options, suppose the current consumer market size is 100 each for the xDSL and the VPN service. Furthermore, suppose the VPN market is fully saturated while the xDSL market is estimated to

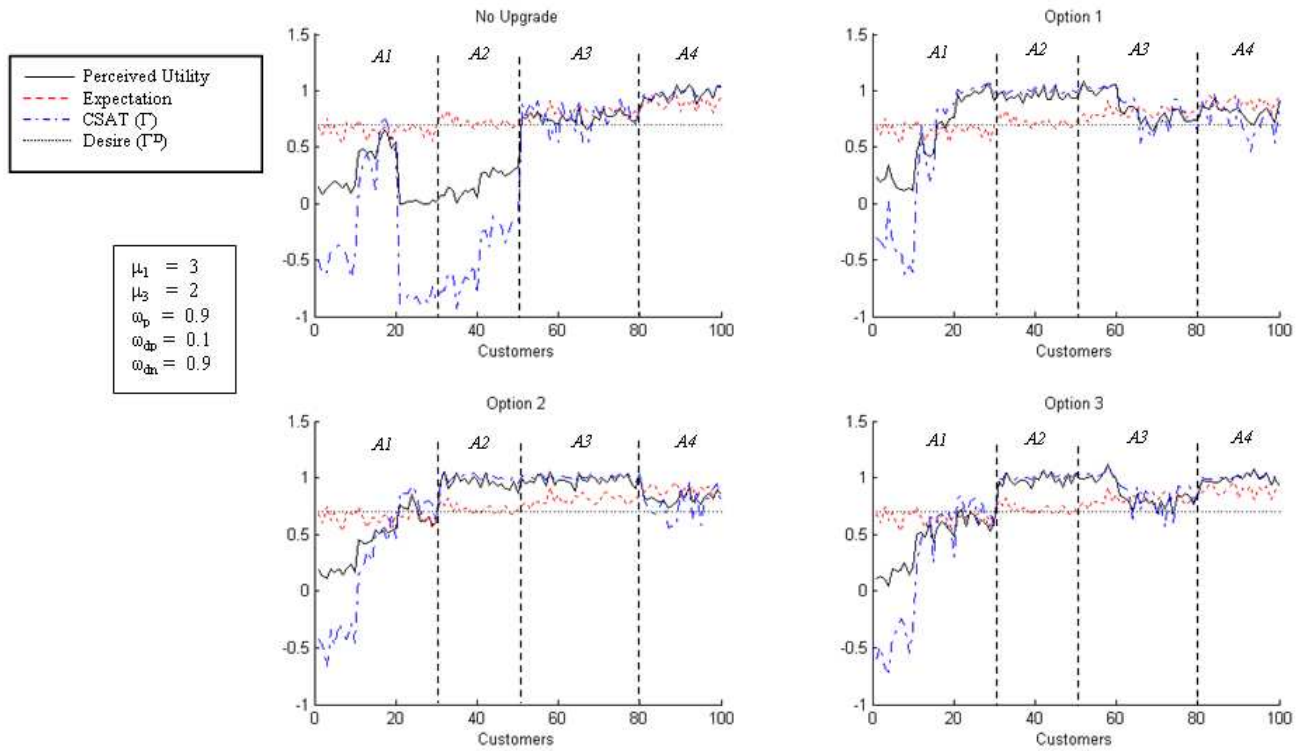


Fig. 12. Customer Satisfaction of Network Upgrades

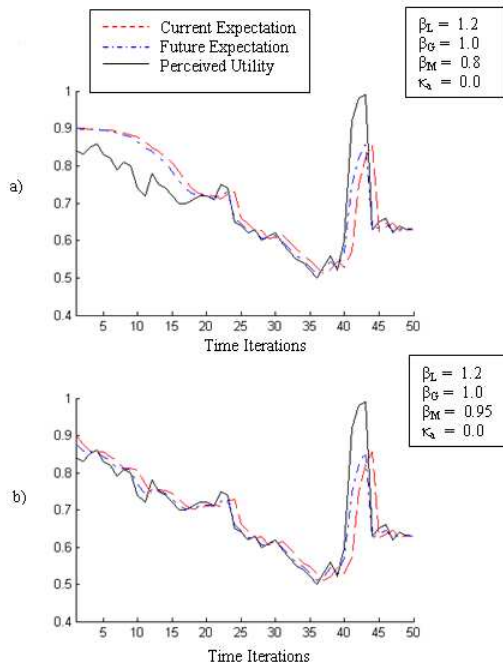


Fig. 15. Experience and Long Term Service Expectation

grow by 80 customers (in practice, this value is projected by the Bass model). Figure 16 illustrates the customer populations and service profitabilities for the three upgrade options. Compared with Figure 13, our model shows that the aggressive xDSL strategy (option 1) is able to attract more

xDSL customers by pushing for better service performance, and hence better future expectation. Thus, depending on the actual earning difference of VPN service over xDSL service, our model may evaluate option 1 as the more profitable option.

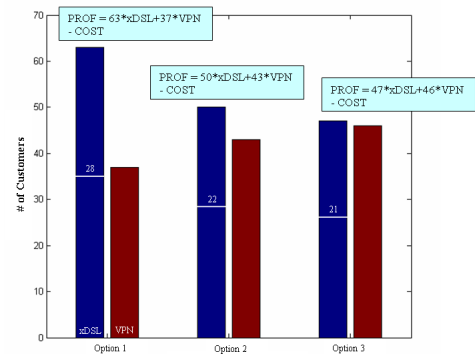


Fig. 16. Customer Population for Different Upgrade Options

In the second simulation case, we conduct a more detailed discussion on how network performance influences customer satisfaction and show an example of how our model could be used in practice. The simulation setup depicts a typical regional service provider network. Three comparative performance analysis of the network infrastructure are presented, each from a different view: link utilization, QoS performance of customer flows, and customer satisfaction. Figure 17 shows the regional service provider network, simulated in NS2. The typical access, transit and core

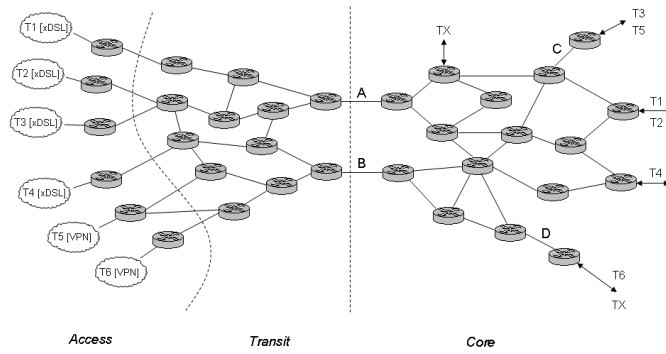


Fig. 17. Simulated topology of a regional service provider network

network topology is recreated. The links in this simulated network are identical in characteristic to the first simulation study. Six customer groups and one transit traffic from a peer provider are studied. Each customer group has a mixture of service types and customer access times with daily traffic shapes similar to Figure 11, we will track a representative customer flow from each population assuming they are a subscriber of either the xDSL or VPN service (noted between brackets in Figure 17) and analyze their behaviors under various conditions. The traffic exchange between the transit and core network is facilitated with two network links A and B. The customer flows from each service population are modelled as an aggregate Pareto flow from customer access to their respective traffic exchange point at the edge of the core network. The flows are routed through least joint paths. As in real world networks, the flows tend to merge around the various traffic exchange points, forming potential bottleneck links. In this simulation study, four such bottleneck links exist: A, B, C and D. Figure 18 illustrates the utilization of each link over 24 hr. period where link utilization measures are taken every minute. The average link utilizations of the entire day are also presented. In practice, link utilization is often used as an indicator for link upgrades or traffic re-engineering. However, as we observe from Figure Figure 18, it conveys no information as to the impact of congestive links on the performance of customer flows.

To analyze the impact of the network utilization on customer flows, we could conduct representative customer flow tracking. In this case, we trace a representative customer flow from each customer population. A representative xDSL customer is traced in each of the population T1 to T4 and a representative VPN customer is traced in each of the population T5 and T6. We consider in this case study that the xDSL customers are offered 330 Kbps (maximum throughput) service while the VPN customers are offered 680 Kbps service. Each traced flow is modelled as FTP over TCP in the simulation and Figure 19 shows the application level throughput measured over a 24 hr. period at five minutes sampling intervals. Delay is not monitored in this case because round trip delays within regional network seldom exceed application requirements. From the throughput

trace, it is apparent that the congestion at link A and B during prime time of the day causes significant impact on customer flows. Comparing the throughput of T1 to T4, T4 seems the least impacted because link A is the only bottleneck link along the flow and trace from T4 has the least shared path with other flows. Comparing T5 and T6, T6 fares significantly worse since in addition to the bottleneck at link B, its traffic also shares link D with transit traffic TX from a peer provider. Upgrade link A and link B appears to be imminent from this analysis. Figure 20 presents the throughput trace after link A and B are upgraded.

The link upgrades produce significant improvement over all the customer traces. However, the traces from T3, T5 and T6 still indicate potential problems especially if T5 and T6 have strong mix of VPN customers over xDSL customers. Besides conducting link upgrades which are cost prohibitive, resource provisioning mechanisms such as service differentiation and network dimensioning could be conducted. In this case, we create service differentiation across link C and D into premium and standard classes (60% and 40% of the link capacity is dimensioned for each class respectively). Traffic from T5 and T6 is thus given precedence over traffic from T3 and TX. Figure 21 shows the result of such dimensioning. We see that the analysis resulting from tracing customer flows yields sensible network upgrade and planning strategies that maximize the performance of the customer flows that hopefully lead to better revenue generation.

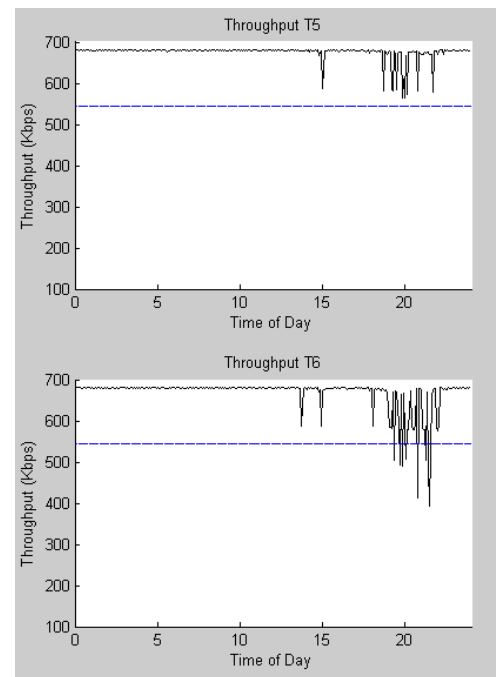


Fig. 21. Throughput Performance After Link C and D Dimensioning

As demonstrated in this paper, improvement in network performance does not produce proportional improvement in customer satisfaction. In analyzing the customer satisfaction of the above trace traffics under varied customer conditions,

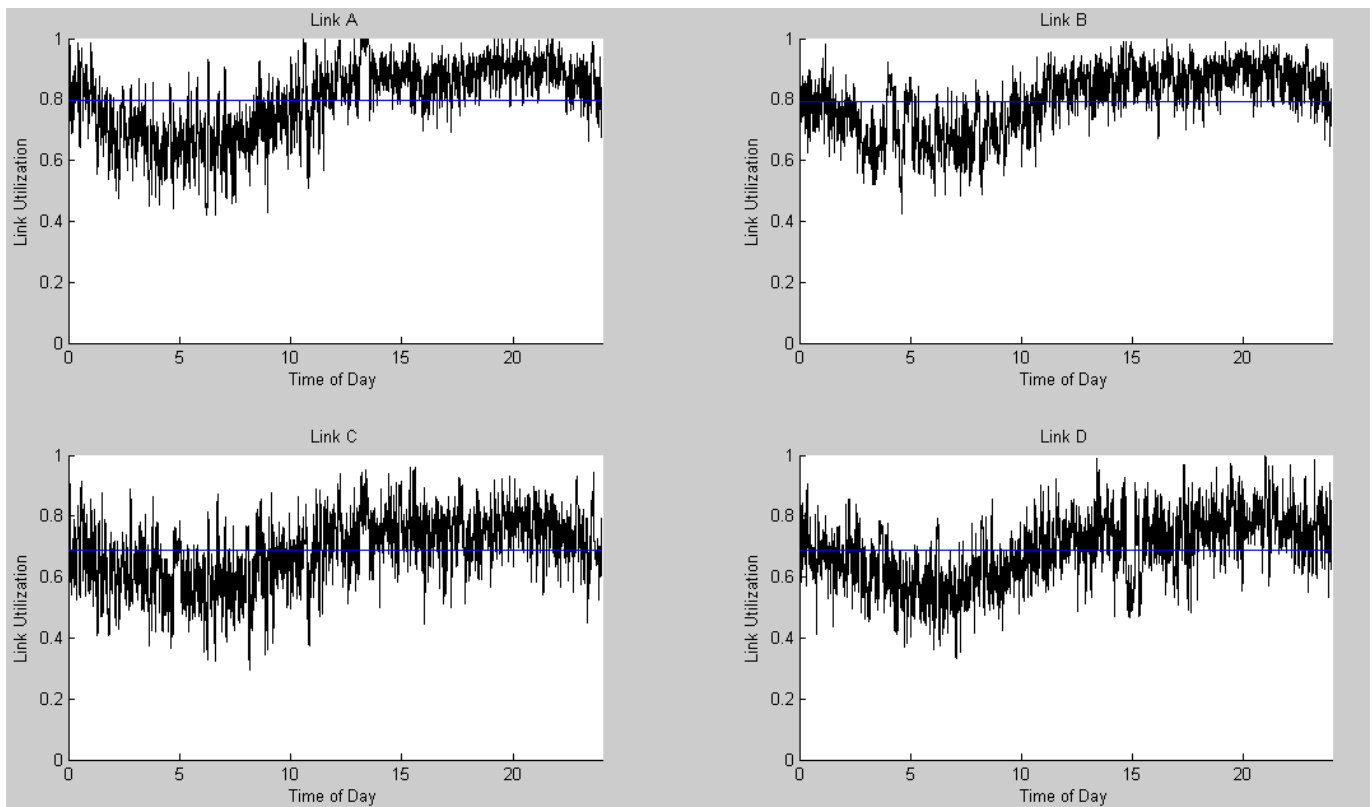


Fig. 18. Link Utilization over 24 hr. Period

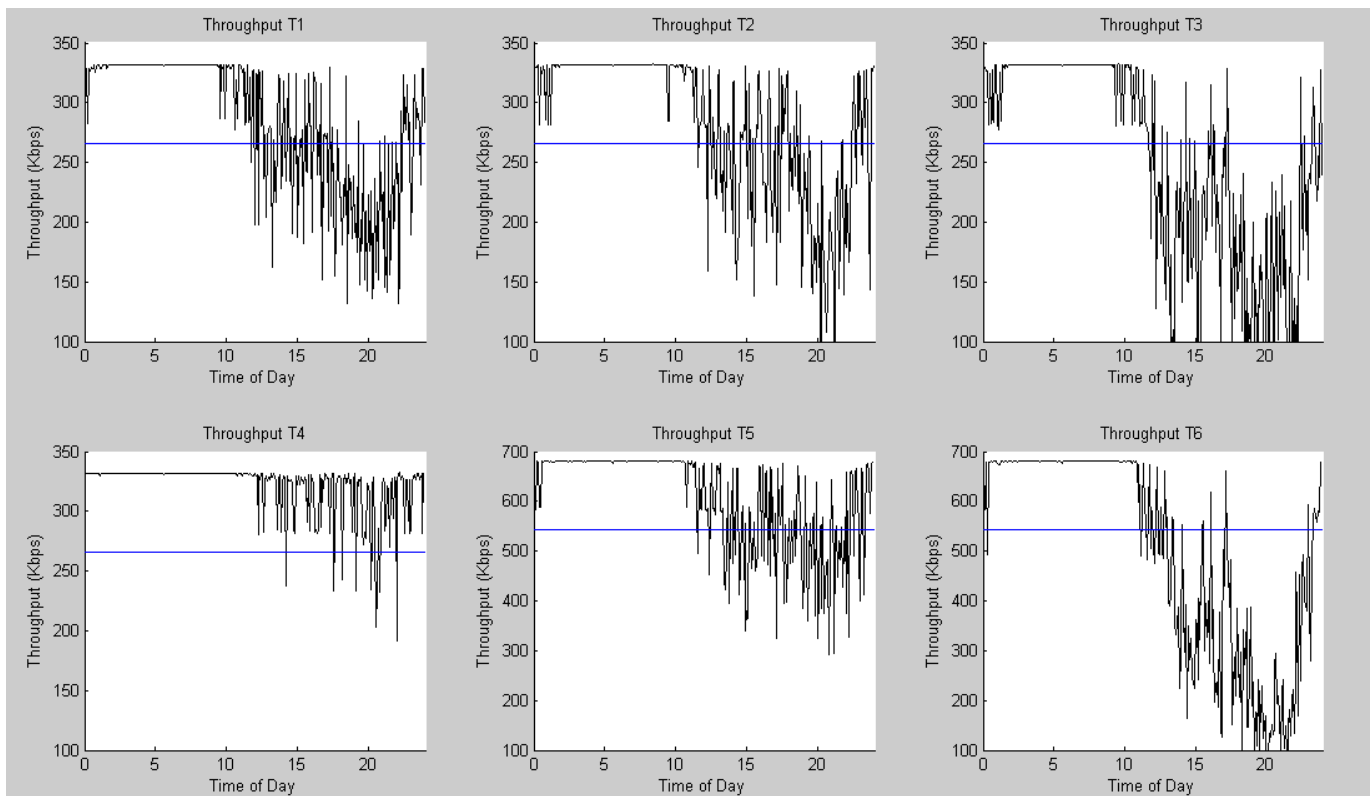


Fig. 19. Throughput Performance of Representative Customer Flows

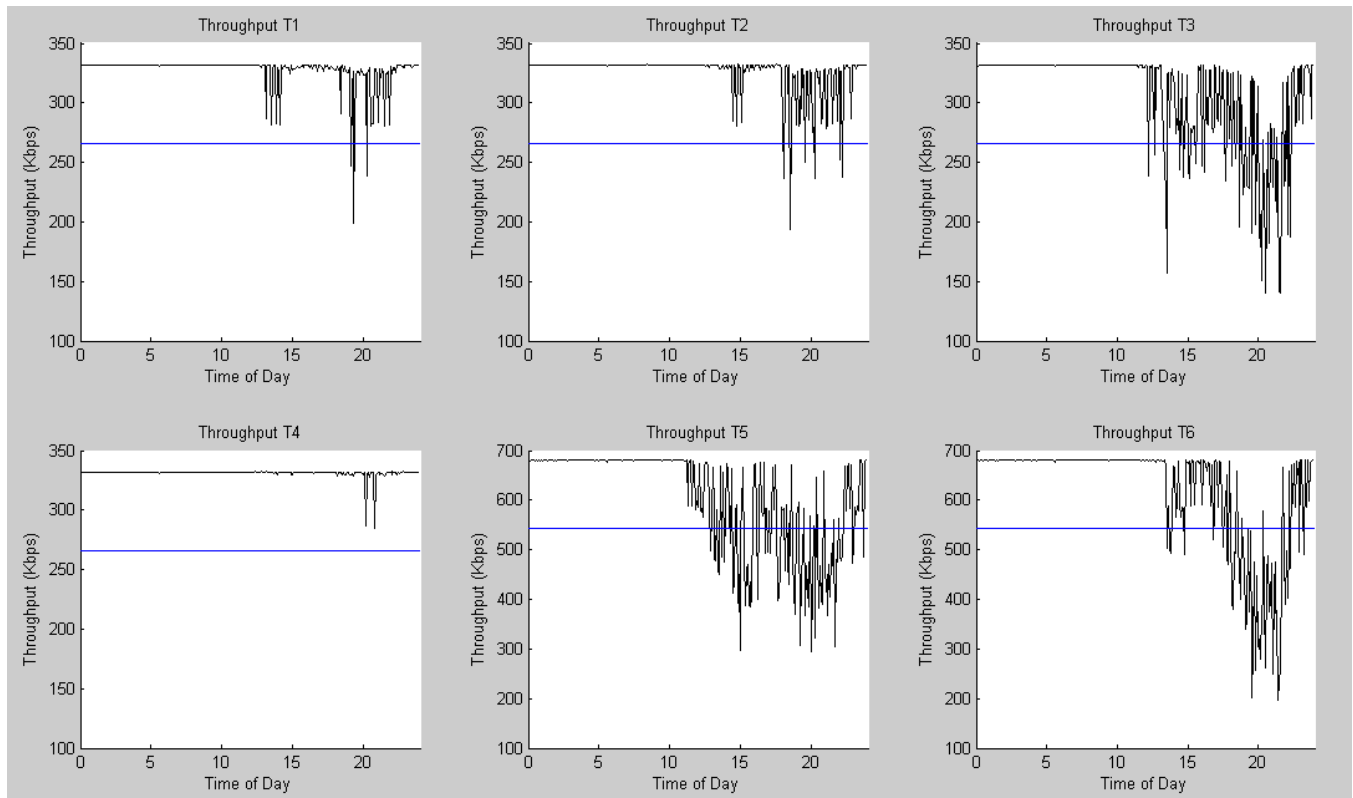


Fig. 20. Throughput Performance After Link A and B Upgrade

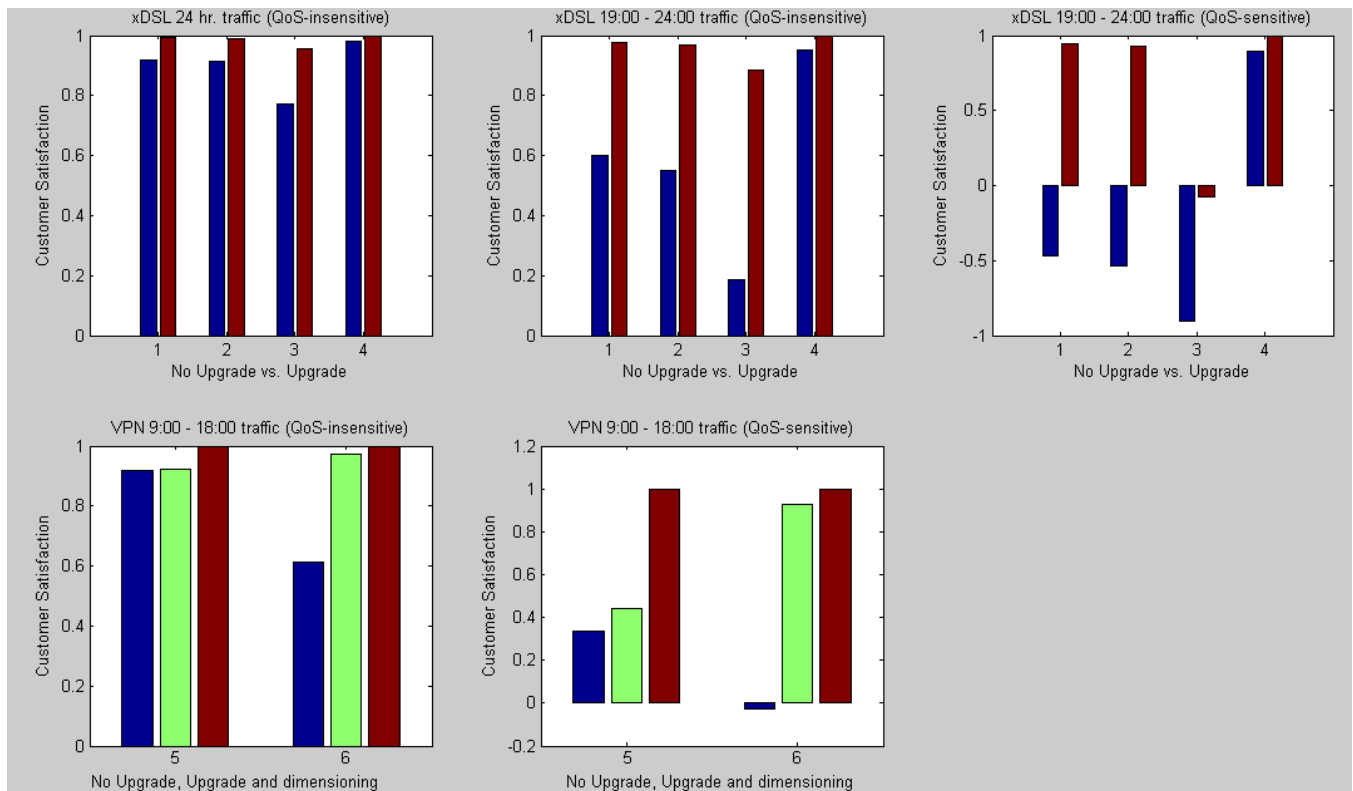


Fig. 22. Effect of Upgrades and Dimensioning on Customer Satisfaction

we study the effect of these enhancement on customers. Figure 22 presents the customer satisfaction under different customer access patterns and QoS sensitivity. For QoS-insensitive traffic (e.g. FTP and P2P) the perceived utility is computed as the ratio between obtained throughput over maximum throughput. For QoS-sensitive traffic (e.g. multimedia traffic), throughput of 266 kbps (for xDSL) and 544 kbps (for VPN) are used as the defective thresholds, corresponding to roughly 80% of the maximum throughput. These thresholds are also depicted in Figures 19, 20 and 21. We compute customer satisfaction with the same modelling parameters as used in the previous simulation setup with customer expectation set at 0.8. As illustrated in Figure 22, the raw computation of customer satisfaction could yield negative values. In practice, these negative values should be set to 0 to obtain the normalized value of Γ , nevertheless they are left here for comparison. The first three set of graphs consider xDSL customers from population T1 to T4. We see that for customers that are QoS-insensitive and access the network 24 hours a day (representation of the permanent P2P population often prevalent in xDSL service), performing link upgrades is of little consequence. This category of customers is satisfied as long as their achievable daily average throughput remains reasonable. However, for the other xDSL users that are the bulk of “prime time” traffic, their satisfaction is severely impacted by link congestion and hence they benefit the most from link upgrade. We note that because T4 does not access the same transit-core link as T1 to T3. It was not significantly impacted by prime time traffic as the others. Hence from the analysis of the xDSL customer satisfaction, it seems that upgrade link A is quite effective given a large mix of prime time xDSL users in population T1 to T3 (which should be the case in practice). For the VPN customers, their access times are generally during business hours. For QoS-insensitive customers, upgrade link B only improves the performance of T6 somewhat, while service differentiation does not yield any visible result. For QoS-sensitive customers, The link upgrade and service differentiation strategies creates very different customer responses. It illuminates a prevailing theory in our model: customer satisfaction is a subjective, comparative evaluation between perception and expectation. In the case of T5, performing network upgrade alone does not raise the customer’s received performance to a level that meets the customer’s expectation and hence despite the actual increase in performance, the customer perceives very little improvement in satisfaction. In the case of T6, the improvement over performance as the result of link upgrade already meets the customer’s expectation, conducting service differentiation in addition does not significantly influence the customer’s opinion of the service. Our analysis indicates that network planning and upgrade strategies should be made with respect to the particularities of the customers to meet customers’ expectations.

VII. CONCLUSION

In this paper, we have presented a new market science approach to assess service profitability of network upgrade

and planning decisions. Our approach captures the intricate interactions among network performance, customer behavior, and market dynamics and is founded on theoretical and empirical studies from market science, economics and psychology. The resulting model produces a series of mathematical processes that are concrete and well-behaved. Following this approach, we detailed the creation of such a generalized analytical model for forecasting network upgrade and planning decisions, providing a set of meaningful parameters to model wide varieties of network service characteristics, customer attributes, and market conditions. Through in-depth case analysis and simulation studies, we show that the best network upgrade option cannot be determined solely based on performance improvements, but is also service, customer, and market dependent. Many of these complex interactions are captured and reflected in our model and are key determinants of service profitability. As we have shown, central to this process are the customers, and it is imperative for service providers to establish service performance on par with a customer’s service expectation, and to develop customer experience over time. In addition, we find that service differentiation and network dimensioning could be effective methods of improving customer satisfaction and hence revenue generation even without the incentive of charging additional service fees to the customers.

In the simulation study, we have shown how our model could be used to analyze practical problems in regional networks through representative flow tracing and customer satisfaction analysis. Furthermore, our prior work [11] demonstrates that through aggregation and pruning, customer performance at the network level is obtainable without relying on detailed customer tracking or minute simulation of large scale networks. Given the intricacies among the modelling parameters, it is imperative to conduct validation and tuning over time in real world SP operations. In market science, when faced with complex models and hypotheses, much of the validation work is carried out over large data sets across long periods of time, where statistical analysis is often helpful in deducing trends and linkages among metrics. We think a similar approach is appropriate to the tuning of our model, in conjunction with simulation studies and numerical analysis. Whereas simulation studies and numerical analysis could shed some light on the sensitivity of the modelling parameters especially those closely related to network performance, much of the work relies on market data such as customer satisfaction and service turnover rate, information not particularly obtainable through mathematics but trackable by SPs in business practices. We think such a process could be an invaluable exercise to the SPs. Experimentation with the model in the network planning and upgrade processes not only provides additional forecasting capability to the planners but also yields outputs (e.g. customer turnover rate) that are comparable with future data. Through an iterative validation and parameter tuning process, the model and its parameters could be evolved and refined over time to suite the particular customer base, service condition, and market environment of the service provider.

The validity of a model and its derivable results are inherently

dependent on the availability of its input data and parameters, and the correctness of the theories that underpin the model. Much care was taken in constructing the model only based on parameters and input data that are tractable, and in many cases known to be available to the SPs. Among the many theories present from market science, we only included the most fundamental and tried ones in the model. The applicability of these theories is confirmed in market studies across many service industries over the past decades. The mathematical forms that we have derived from these theories are intentionally designed to be simplistic, with flexible parameters to ensure that the model is tunable to the particularities of the service provider and market scenario.

Theoretical studies aside, we will further validate and refine our approach based on real world SP operations and market data. We foresee such study could be a long term process (e.g. 5 years) but would be highly beneficial to the network service industry. A number of future works extend from this model, such as the incorporation of performance related service charging and penalty functions in the profitability computation, the likelihood of the customers to reinstate a service provider they have previously turned away, and the effect of provider competitions (e.g. pricing difference, technology competition, advertisement effects). We believe our approach brings a unique perspective to the network upgrade and planning research and the resulting models are general enough to benefit many network service related analysis processes, such as service infrastructure design, management, network dimensioning, and others.

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