Bandwidth in SFDC

SHAKTI SINGH RAJPUT
Department of Computer Engineering, Poornima College of Engineering, Jaipur

Abstract -- Salesforce is intended to use as very little information measure as attainable, in order that the positioning performs adequately over high-speed, dial-up, and wireless net connections. Whereas average page size is on the order of 90KB, Salesforce supports compression as outlined within the communications protocol one.1 commonplace to compress the hypertext mark-up language content before it's transmitted as knowledge across the net to a user's pc. the positioning was designed with minimum information measure necessities in mind, thus the in depth use of color committal to writing rather than pictures. Our average user is also far-famed to look at roughly one hundred twenty pages from our web site per day. However, it's best to live any page that has been tailor-made, particularly if Visual Force parts are acquisitions to the page, to urge Associate in nursing correct measure of the page size. Our application is homeless, therefore, there are not any communication necessities within the background once the page masses like ancient shopper server applications e.g. Outlook. Therefore, once the page masses there are not any extra information measure necessities till a user queries or writes information to Salesforce. In practice we have found the bandwidth requirements for other commonly used programs place a much higher demand on Internet bandwidth. We have also found through working wit. An example would be an Account Executive sending a 7MB marketing brochure or PowerPoint presentation to a customer. The application of the formula "Peak bandwidth/number of users = average bandwidth per user" does not accurately portray the average bandwidth usage by the average user at Salesforce.

I. INTRODUCTION

We have found the bandwidth requirements for other commonly used programs place a much higher demand on Internet bandwidth. We have also found through working with our customers that email (business & personal), email attachments, News, streaming video, stock update, place a much greater strain on the available bandwidth. Hence, we recommend the customer measure all activities to make sure they are evaluating a holistic demand on their network services. An example would be an Account Executive sending a 7MB marketing brochure or PowerPoint presentation to a customer. The application of the formula "*Peak bandwidth/number of users = average bandwidth per user*" does not accurately portray the average bandwidth usage by the average user at Salesforce. Salesforce handles considerably more transactions per second in aggregate from all our customers than any one individual customer would see from their end (since not all users would be actively loading pages simultaneously). In short, it is difficult to specify customer bandwidth because of the nature of the Internet and individual corporate usage. Network latency, peering issues, bandwidth at upstream providers, users using their Internet connections for other use besides

II. PROBLEM DOMAIN

This error happens throughout any set (log-in, sync, log-out). Salesforce uses a web site as a portal between the information within the cloud and therefore the robot devices. If the request of websites is exceeded, Error 00001 can occur and set would be incomplete.

III. OBJECTIVES & SCOPE

Objective: To find the solution of error 00001 in salesforce.

IV. LITERATURE REVIEW

Montgomery and Urban (1969) and Lucas et al. (1975) use profit maximization models to solve for the optimal salesforce size. A limitation of their approach is that they ignore the presence of multiple products and/or territories. Lodish et al. (1988) use a more sophisticated approach to modeling the issue in the case of one particular firm. They showed, for this one firm, that adding salespeople and redeploying them would result in increased profits. Zosters (1976), Lodish (1976, 1980), Ramaswamy et al. (1990), and Mantrala et al. (1992) consider the problem of finding the optimal allocation of salespeople to territories, products or customers. These studies use static frameworks that do not incorporate learning effects within the salesforce. Another issue that has not been addressed adequately in the literature is specialization and the effect it has on structuring the salesforce. Given that salespeople often specialize in particular products and that such specialists are scarce, there are instances when a non-specialist serves a customer, which may have an impact on sales.

Dewan and Mendelson (1990), Stidham (1992) and So and Song (1998) are examples of works in which both capacity and pricing are endogenous to the firm's decision problem. In all of these, the firm is modeled as a single server queue and capacity is determined by the service rate. In this paper, we are explicitly modeling capacity as the stamng level in a multi-server queue. Furthermore, we consider the interaction of parallel queues serving different customer types. Finally, in our model price determines the sales quantity rather than the customer arrival process. As we mentioned in the Introduction, our formulation is appropriate for environments in which sales leads are "handed off" to the salesforce.

V. BASE PAPER METHODOLOGY AND DESCRIPTION

Model Formulation:

Consider a firm that sells two products, A and B, and has two types of salespeople, A and B. We assume that sales leads representing customers interested in each of these products arrive according to a Poisson process with arrival rates of XA and XB respectively. In the following, we refer to customers and sales leads interchangeably. We can state the profit function of the firm in very general terms as a function of the stamng S = (SA, SB) and the price of each product p = (PA, PB) as follows:

$$\text{fl}(S, P) = \sum_{i=A,B}\sum_{j=A,B} \text{rijCIij}(\text{Pi} — \text{CD} — \text{dlSl},$$

where r.ij is the throughput of type-i leads through typej salespeople, qij is the expected quantity of a product i sold by a type j salesperson pursuing a type-i lead, Ci is the production cost of each unit of product i and di is the cost per unit time of each salesperson. Both Ci and dt are exogenous parameters. The following sections describe how we find the throughput of each customer type (rij) and the quantity sold (qty).

Throughput statistics: -

Salespeople. every employee may match on several leads at the same time with a selected lead being active for days, weeks or months relying upon the character and characteristics of the merchandise category. As we have a tendency to mentioned within the Introduction, it's common for salespeople to be appointed primary responsibility for one set of product and secondary responsibility for others. for instance, in salesforce compensation is usually designed as a matrix that assigns a commission to sales person type and product-type pairs. the aim of such a matrix is to encourage salespeople to specialize in their primary product lines whereas keeping the choice open for cross-selling. To modify our analysis, we have a tendency to assume that the assignment of consumers to salespeople happens as follows. once a type-i sales lead arrives it is directed to a type-i salesperson. However, if all type-i salespeople are busy pursuing other leads the lead is routed to a type-j salesperson.

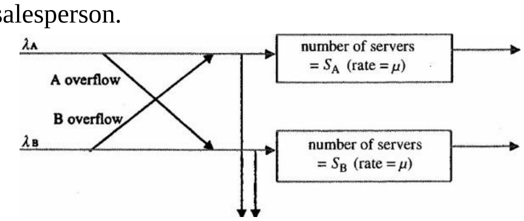


Fig. 1. Routing of leads through a hierarchical salesforce.

We are modelling the salesforce as a pair of multi-server service systems with exponential service times that operate in parallel and receive their own independent Poisson arrival streams with rates XA and AB but also allow leads to overflow into each other. Later we will also examine systems in which a group of salespeople are dedicated to a single product. Because the "single-product" model is relatively simple (e.g., the sales leads flow through an M/ M/S/ S queueing system), we will focus on the more general two product model here. We will assume that the service rate of each salesperson, g, is the same (although it is not difficult to relax this assumption). Note that we are modelling each lead as being processed sequentially by a salesperson while in practice a salesperson would be pursuing multiple leads simultaneously. We make this abstraction to simplify the calculation of queueing statistics, and we believe that explicitly modeling the simultaneous processing of leads would be an interesting topic for further research. In addition, we assume that sales quantity does not affect the time it takes to pursue a sales lead.

The sales quantity model described in the next section uses two sets of statistics from this model: throughput and utilization. Let rAB represent the throughput of type A leads through type B salespeople; rBA, rAA, and rBB have similar interpretations. Note that ro is a function of the stamng vector S = (SA, SD. Utilization is represented as PAB, PBB, PAA, and PBA, and each of these is calculated easily from the appropriate values of ry.

Calculating the throughput statistics of the salespeople is more difficult than finding the throughput of a standard loss system because the arrival process to each group of salespeople is not purely Poisson but is instead a combination of a Poisson process and bursts of arrivals that are sent when the other sales group is fully occupied. For this system we calculate throughput statistics numerically. Specifically, we define a two-dimensional state space (NA, NB) where NL represents the number of busy salespeople of type i. The balance equations for this state space are relatively simple to enumerate, and we use these equations to solve iteratively for the steady-state probabilities of (NA, NB) (Gross and Harris, 1985, p. 437). Given the steady-state probabilities, we calculate the expected throughput and utilization.

3.2. Quantity sold

The quantity of the product sold as a result of pursuing a lead depends upon the price of the product and the experience of the salesperson with that product. Here we develop a model of demand that is based upon customer sensitivity to both price and the experience of the salesforce as well as a model of the career path and experience accrual of an individual salesperson.

Given that a type-j salesperson pursues a lead for product i, we assume that the sales generated by that lead is a random variable DIJ = ay — ßiPi, where aij is a random variable that depends upon the (random) experience level of the salesperson encountered by a customer and ßi is the sensitivity of demand to price for product i. Therefore, in the profit function of Equation (1):

qty = E[Dlj].

The important difference between our specification and the traditional, linear demand model is that we allow the intercept to vary across salespeople. In the marketing literature sales volume is typically described as a function of the skill of a salesperson. Rao (1990) for example, proposes the functional form:

$$s = so(l — e^{nb}), \qquad (2)$$

where s is the sales, so is the maximum achievable sales level, b is the skill of the salesperson and n is a parameter determining the rate at which so is approached. From the learning-curve literature (Yelle, 1979; Badiru, 1992), we can see that often heterogeneity in skill is a result of heterogeneity in experience levels. In this paper we combine these two perspectives by expressing sales volume as a function of experience. We use the same functional form as in Equation (2), in particular we assume that atj = Kij(l — exp(—nw,j)) where Wij is the accrued experience of a type-j salesperson selling product i (measured in units of time), Kij is a constant representing the upper limit of sales ability, i.e., the sales volume of a salesperson with infinite experience, and n is a learning parameter. Much of the traditional literature on learning curves uses units of work, for example widgets built, as a measure of experience. In manufacturing settings where unit labor costs decrease with learning because workers become faster, and it is easy to measure costs, this approach is appropriate. In our application the work unit is a sales lead and it is difficult to obtain data on the number of leads handled. Furthermore, it is not clear that the time spent per lead will decrease with experience. Rather, as we model it, the likelihood of a sale will increase with experience.

Therefore, additional experience selling a product has the effect of increasing the intercept of the demand for that product. This functional form is appealing for a number of reasons. First it is consistent with the marketing literature, second, it is consistent with the learning-curve literature in which most learning curves are asymptotic, and finally we have found that it provides a reasonable fit to actual salesforce performance data. The learning-curve literature typically models production costs as a decreasing function of experience that asymptotically approaches zero. In our case we are modeling the effect of experience on sales (or revenue generation) and therefore use an increasing function of experience that asymptotically approaches some upper limit. Note that the proposed function differs from the unbounded "power function" used in Pinker and Shumsky describe between experience and

Given our discussion above we can now define quantity sold as:

$$D_{ij} = \text{Kzj}(1 - e^{-nw_{ij}}) - \beta_i p_i. \qquad (3)$$

Let y be the tenure of a salesperson. Then the expected sales quantity is:

$$q_{ij} = = \quad \text{Kij} \quad {}_{-}K_{ij}E_y[E[e^{-nw_{ij}} \quad \text{I} \quad -$$
ßiPi. (4)

It can be shown that when the average time spent on a sales lead is small relative to the tenure of a salesperson then E[exp(I y] can be closely approximated by $\exp^{(-}$

This approximation is similar to one that appears in Pinker and Shumsky (2000) and its accuracy here has been verified using simulation. Therefore: ^{ij}Kij(l — e¯'1Pijt— ßlPi).

The probability density function for y, gy(t), is derived from a model of a salesperson's tenure process in which a career is divided into stages, so that the stages of the career can be modeled as states of a continuous-time Markov chain. The tendency to end employment (by being fired or quitting) varies from stage to stage, and the time a salesperson stays in a stage before leaving is exponentially distributed. The parameter Xl is the rate at which salespeople move from the first stage to the second stage, X2 is the rate at which they end their employment in the first stage, X3 is the rate at which workers in the second stage end their employment, and 12 > 13.

Using this model of the tenure process it can be shown that:

$$_{ij} \approx K_{ij}\frac{n\rho_{ij}}{\lambda_1+\lambda_2+n\rho_{ij}}\left(1+\frac{\lambda_1^2+\lambda_1\lambda_2}{(\lambda_1+\lambda_3)(\lambda_3+n\rho_{ij})}\right)$$
— ßiPi.

(6)

Equation (6) accounts for price, learning and the tenure process to determine the quantity sold. Since Pij is a byproduct of the staffing levels, S = (SA, SB), Equation (6) also links staffing to sales.

3.3. The complete objective function

We can now restate the optimization problem faced by the firm as:

Max ms, p)

where

rl(S, p)

$$= \sum_{i=\mathrm{A,B}}\sum_{j=\mathrm{A,B}}\left\{r_{ij}(\mathbf{S})\left[K_{ij}\left(\frac{r_{ij}(\mathbf{S})}{\mu S_j}\right)\times\left(\frac{n}{\lambda_1+\lambda_2+n(r_{ij}(\mathbf{S})/\mu S_j)}\right)\times\left(1+\frac{\lambda_1^2+\lambda_1\lambda_2}{(\lambda_1+\lambda_3)(\lambda_3+n(r_{ij}(\mathbf{S})|\mu S_j))}\right)-\beta_i\mathbf{p}_i\right](\mathbf{p}_i-c_i)-d_iS_i\right\}. \qquad (7)$$

There are a number of tradeoffs explicitly represented in this objective function. First we know that throughput (rij) is increasing in staffing and therefore there is a trade-off between the additional revenue brought by increased staffing and the marginal cost of an additional salesperson di. However, while increasing staffing increases the number of sales leads that can be pursued, increasing staffing also reduces the number of units sold per lead because it reduces the utilization and therefore the experience of the salesforce. This complex effect of utilization on experience and profits can be seen by the appearance of the variable

S in the denominator of some of the terms in Equation (7). This trade-off is clear when the salesforce sells a single product. In Section 6 we will see that this utilization effect also has a significant influence on salesforce design decisions when there are multiple products, e.g., whether to deploy a specialized or pooled salesforce.

4. Optimizing prices, given salesforce size

The complex interactions among staffing, sales and experience make it difficult to derive an analytical characterization of the optimal decision. However, given the expected profit function, Equations (1) and (7), it is relatively straightforward to solve for optimal prices given a specific staffng of each type of salesperson.

To obtain the optimal prices given staffing we differentiate expected profit, Equation (l), with respect to price and obtain:

$$\sum_{j=\mathbf{A},\mathbf{B}} \left[r_{ij} \frac{\partial q_{ij}}{\partial p_i} \right.$$ (Pi — CD + rijqij

$= 0 \quad \text{for } i = \text{A, B.}$ (8

Solving for price and using the notation of Equation (7) we find:

$$p_i = \frac{c}{2} + \sum_j r_{il} K_{ij} \left(\frac{r_{ij}(\mathbf{S})}{\mu S_j} \right) \left(\frac{n}{\lambda_1 + \lambda_2 + n(r_{ij}(\mathbf{S})/\mu S_j)} \right) \times \left(1 + \frac{\lambda_1^2 + \lambda_1 \lambda_2}{(\lambda_1 + \lambda_3)(\lambda_3 + n(r_{ij}(\mathbf{S})/\mu S_j))} \right) \Big/ 2\beta_i \sum_j r_{ij},$$

for i = A, B. (9)

This expression is similar to the standard monopolistic price for a linear demand curve, except that the intercept is a weighted average of the intercepts of the two sources of demand. If there were only one product, no learning effects (so that the demand intercept is a constant, a), and throughput were equal to one, then the price equation is:

$$p = \frac{c}{2} + \frac{\alpha}{2\beta},$$

which is the standard monopoly price.

We now describe a few properties that follow directly from the price equation. The price of product i,

l. increases with the cost, Ci, of product i;

2. increases with the maximum productivity, Kij, of a type-j salesperson with product i;
3. decreases with the price sensitivity ßi, of product i;
4. increases with the learning rate, n (while this is not obvious from Equation (9), it can be shown that apt•/0n > 0).

One property we do not specify here is the relationship between staffing and pricing. While it might seem appropriate to conjecture that prices and stamng (for a given product) move in the same direction, this is not clear from our model. While throughput is increasing in staffing, utilization is not, and this may create a non-monotone relationship between the two. We revisit this issue in the numerical experiments of Section 6.

5. Industry data analysis

The model described in Section 3 assumes that sales productivity grows with the experience of a particular salesperson. While the impact of experience on manufacturing productivity has been well documented by empirical research (see the summary by Yelle (1979)), to our knowledge there have been no published studies linking sales and experience in a salesforce. The data analysis in this section helps us to identify reasonable learning-curve parameters that will be used in the numerical experiments of the next section.

For our analysis we have obtained sales data from one particular company, "Firm A," a market leader in offce products with an annual sales revenue of over $10 billion and over 40 000 employees. Although the firm operates in various product and service markets we restrict our focus to the division that is the flagship of the company and accounts for a substantial proportion of its revenues. The business environment of this division conforms to the assumptions of our model: the firm is a market leader and has some pricing power, the product is complex, and the market is mature so that salespeople primarily respond to requests from existing customers, rather than finding new leads. The division has two primary salesforces, "Representatives" (or "Reps") and "Specialists". Specialists sell technologically advanced, high-priced equipment to large corporations while Reps focus on less-complex and less expensive products for small and medium-sized firms. Our data set is cross-sectional: it records the number of years a salesperson has been with the firm (tenure) and the most recent annual sales figure for each employee. Table I contains a summary of the data. Figures 2 and 3 display the relationship between tenure and sales in each sale force. Each 'e' in Fig. 2 represents the average sales of 50 salespeople, while each data point in Fig. 3 represents a group of 40 salespeople. For example, the first point on the lower left of Fig. 2 shows the average sales of the 50 most inexperienced Reps: their average tenure was 5 months, and the average sales in that group was $330 000/year. In the figures we see a relationship between tenure and sales that could be attributed to learning, and that in each salesforce there is a large number of relatively inexperienced salespeople on the "steep" part of the learning n = 0.02 (in this cage, a salesperson reaches just 20% of the maximum after I year and requires almost 17 years to reach 98%). On the other hand, some products and markets are relatively simple, so that salespeople have a rapid ascent up the learning curve, relative to their tenure. After this rapid climb, sales do not increase significantly with experience. To represent such environments we use upper bound of n = 4 (a salesperson reaches 98% of the maximum within 1 month).

While the estimates of N derived from the industry data lead directly to our estimates of n in the general model, the connection between H and the parameter K is more complex. There are two complications when trying to derive K from H: (i) K represents a quantity of product sold per sales

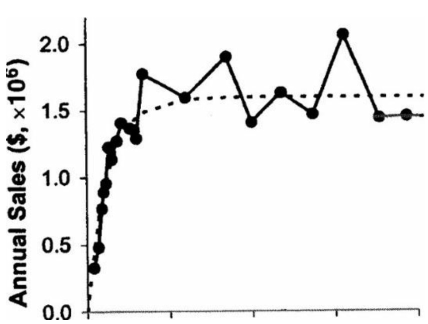
Table 1. Summary of salesforce data

		Employee tenure (years)				Annual sales per employee ($, x 10^6)			
Salesforce	Number ofemployees	Mean	Std. dev.	Min.	Max.	Mean	Std. dev.	Min.	Max.
Reps	1239	9.1	9.3	0.1	35.6	1.3	1.1	0.005	9.5
Specialists	409	10.0	7.8	0.2	34.8	3.1	2.2	0.005	14.9

salesi = — e NT) + (10)

where salesi represents the dollar value of sales made by a salesperson i, Ti is the length of tenure, and is a stochastic error term assumed to be distributed identically and independently normal with mean zero. We used the maximum likelihood method to estimate H and N from each data set. These estimates are presented in Table 2 and the associated functions are plotted as dotted lines in Figs. 2 and 3. As one might expect, the learning curve is more gradual and the asymptote H is higher for the specialists, who handle more complex and expensive products.

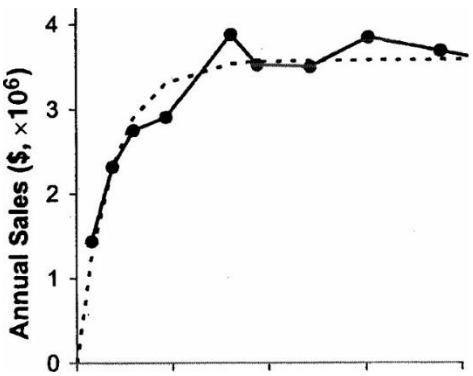
The proposed model seems to provide a good fit with the data, although there are clearly other factors besides experience that influence sales ($R^2 = 0.10$ and 0.11). There are also some limitations to this data set that restrict our ability to precisely estimate the learning-curve parameters n and Kij (or, K when there is just one product).



O 5 10 15 20 Tenure (years)

a

lead, while H is an upper bound on the annual sales per salesperson; and (ii) K is the number of items sold per lead, given infinite sales experience and a price of zero (see



o 5 10 15
20 Tenure (years)

Fig. 3. Specialists data and model.

Table 2. Maximum likelihood estimation results

Salesforce	Parameter	Estimate	Std. err	T-stat	P-value
Reps	H	1596 065	35 655	44.8	<0.0001
(R^2 = 0.10)		0.066	0.0083	8.0	<0.0001
Specialists	H	3579 766	124986	28.6	<0.0001
(R^2 = 0.11)		0.046	0.0011	4.44	<0.0001

Equation (3)). To overcome complications (i) and (ii) we make a few additional assumptions and then find a value of K that is consistent with the observed sales data. Details of this procedure are included in the next section. In practice, however, a firm's prices, cost per unit, and quantity sold are often observable, and these data can be used to more directly estimate the cost and demand parameters of the model.

6. Numerical experiments

Here we explore the interactions among the exogenous parameters of the model (e.g., learning rate, price sensitivity and cost parameters) and the endogenous decisions (staffng levels, prices, and routing decisions). In Section 6. I , we describe baseline parameters for the model that are derived from the analysis of Section 5 and are used in subsequent comparisons. In Section 6.2, we find the optimal staffing levels for a single-product system, given the baseline parameters, and we see how the optimal staffing level changes as the cost, learning curve, and productivity parameters change. In Section 6.3 we consider a firm with two products and two salesforces and investigate the relative benefits of a pooled salesforce versus a system with two completely specialized salesforces. We also examine the impact of the routing decision within a pooled salesforce by comparing two sales-lead assignment procedures: (i) random assignment; and (ii) the assignment of primary and secondary products to each salesperson, the hierarchical system described in Section 3.1.

6.1. Baseline scenario

The parameters for the baseline scenario are based upon the sales "Rep" data from the previous section.

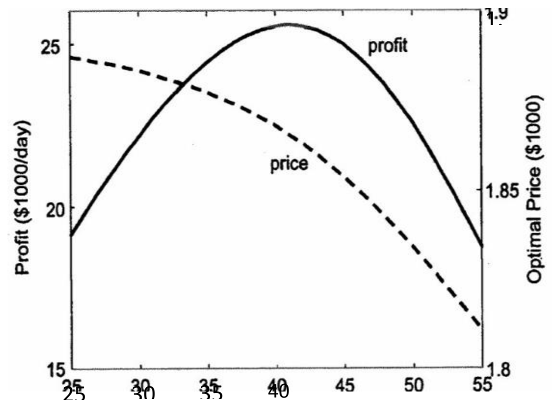
- From the analysis above, n = 0.066 in the baseline model. However, we will vary n from 0.02 to 4.
- The tenure parameters (Xl , 12, and 13) have been set so that the distribution of tenure found by a random arrival to the system is similar to the distribution of tenure in the Rep data set. In particular, the model is configured so that the average tenure of a sales Rep seen by a customer is just over 9 years, with a large percentage of relatively inexperienced salespeople: 52% below 4 years.
- d = \$350/day. This is the average rate of compensation in the industry.
- β= 2. Below we experiment with a range of ß and describe the impact of changes in ß.
- μ= 1 /day for all products and salespeople. According to the industry data, the average total time spent on a single lead is approximately I day.
- X = 40/day. The size of an entire salesforce can often be measured in the thousands, but an offered load (X / g) of sales leads equivalent to 40 salespeople corresponds to a medium-sized regional salesforce for

a single product. In Section 6.2, we will consider the salesforce for a single product taken in isolation, with X = 40/day, while in Section 6.3 we apply our model to two products sold by two salesforces. In the two-product case we assume that all parameters for each product and salesforce are equal to the baseline parameters described here, except that XA = XB = 20/day (for a total load of 40 on the system). To simplify the exposition we are reporting results of experiments with a completely symmetric system in which the parameters for each salesforce and product are the same. We have conducted numerous experiments with asymmetric systems without revealing any major additional insights.

Unfortunately, the data set described in Section 5 does not contain sufficient information to find c or K. The model developed from the industry data does indicate that the average Rep, given essentially infinite experience, can earn $1600 000 in annual revenue. Under our assumption that the average lead requires I day of work, and assuming 250 workdays/year, these most experienced Reps average $6400 in revenue per lead. To use this information to find the maximum possible quantity of product sold per lead (K) and the cost per unit (c), we must make two additional assumptions. Assume that firm A: (i) uses the optimal price, as described in Section 4; and (ii) earns a 25% margin on its sales (including the cost of the sale force itself). Then, K = 7.2 and c = $1120 are the only parameter values that are consistent with these assumptions, the parameters above, and the observed maximum revenue of $6400/lead. These values were found by "reverse-engineering" the model described in Sections 3 and 4. While useful as a baseline, we will also experiment with a range of both K and c.

6.2. A single product

First we consider a firm with a single product to sell and a single salesforce. For the single-product case, the objective function of Equation (7) has a single term in the summation, and the subscripts i and j are removed (e.g., Kij replaced by K). Throughput and utilization statistics are calculated from the Erlang-B formula. Given the baseline parameters, we find the optimal price (Equation (9)) and total profit (Equation (7)) as a function of salesforce size, S. The results are shown in Fig. 4. The optimal price is



Size of Salesforce

Fig. 4. Profit and price as staffng varies in the baseline model.

$ 1870/ unit, the profit-maximizing stamng level is 41 sales representatives, and the optimal profit is $25 000/day. We examined the objective function for hundreds of cases and in each case the objective function was unimodal. This was true for both the one-product and two-product scenarios. However, to be thorough, all results presented here were found by searching for the optimum over the entire range of reasonable staffing configurations.

In Fig. 4, large unit profits explain the rapid rise in profitability on the left-hand side of the graph: as we add salespeople, throughput, r, rises and profits increase. This increase is partially balanced by the cost of each additional sales representative. However, in this baseline case d = $350, and the decrease in profits on the right-hand side of the graph is much more rapid than the rate implied by d. In this case, the primary cost of additional servers is the decrease in the utilization of each server and the concurrent decrease in experience. As utilization decreases, both the demand-curve intercept and the optimal price decrease (see Equation (9)). Here the utilization effect first described at the end of Section 3 has a strong impact on both the profit and the size of the optimal salesforce. We also see, in Fig. 4, that the optimal price decreases with the size of the salesforce. We found that this was the case in all our numerical experiments. This observation is consistent with intuition: as we increase staffing we want to increase volume and therefore must decrease prices.

To determine the impact of cost, productivity and learning parameters on the optimal levels of staffing, we varied each model parameter over a wide range around the baseline value described above. For example, took on values from one-half to three. With ß = 0.5, the customer is barely price sensitive and the firm's profit margin is high (80%), given the other baseline parameters. With = 3, the consumer is extremely price sensitive, and given the other baseline parameters the firm cannot be profitable (in this case, the optimal size of the salesforce is zero).

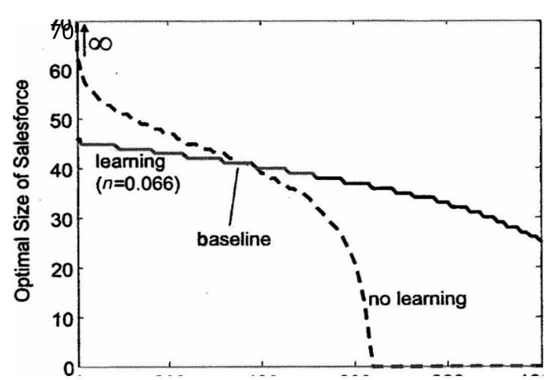
Table 3. Effect of exogenous variables on the optimal salesforce size

Parameter	*K*	*c*	*β*	*d*
Direction of change of the optimal salesforce size as the parameter increases	+	−	−	−

For each parameter combination, we solved for the optimal salesforce size. In all, we conducted over 100 000 of these numerical experiments (contact the authors for a detailed description of the parameters used). For five of the parameters the impact on optimal staffing levels was monotonic. These results are presented in Table 3. In the table, a + (—) indicates that the optimal salesforce size is non-decreasing (non-increasing) as the parameter increases.

These results are intuitive. The impact of K, the productivity parameter, is positive for salesforce size. Because K increases the demand intercept term, an increase in K leads to an increase in salesforce productivity thereby making the addition of salespeople profitable. On the other hand, an increase in the cost of the product, c, has a negative impact on salesforce size. Again, this is because an increase in product cost decreases the marginal revenue gained by adding an additional salesperson. A similar pattern is seen for the price sensitivity parameter, p: as price sensitivity increases, price goes down, and this diminishes the marginal revenue of each salesperson. This leads to a decrease in the salesforce size. An increase in d, the cost of a salesperson, reduces the optimal salesforce size. Finally, an increase in n both increases salesforce productivity and reduces the impact of the utilization effect described above. Both of these effects lead to an increase in salesforce size. However, we will see in the next section that the optimal salesforce size may not be monotone in n when the salesforce handles two products, rather than one product.

In addition, the existence of a learning curve for the salesforce can affect the impact of changes in other parameters; if altering a parameter changes staffing levels, then learning can dampen this effect. For example, in Fig. 5 we see the optimal salesforce size under a range of compensation rates for our model with learning (the solid line) and for a model without learning (the dashed line). In the model without learning, salesforce productivity is fixed so that the two models have the same optimal staffing level, given the baseline parameters. The figure shows how an increase in the cost per salesperson leads to a decline in the optimal salesforce size (as suggested in Table 3), and the figure also shows that the rate of decline is much more gradual, given employee learning. This is because any reduction in staffing also increases utilization. Therefore, in an environment with a learning curve, the marginal contribution of each salesperson is larger and the optimal number of salespeople remains high as d grows. We found a similar effect as we varied



o 200 400 600 800 1 000

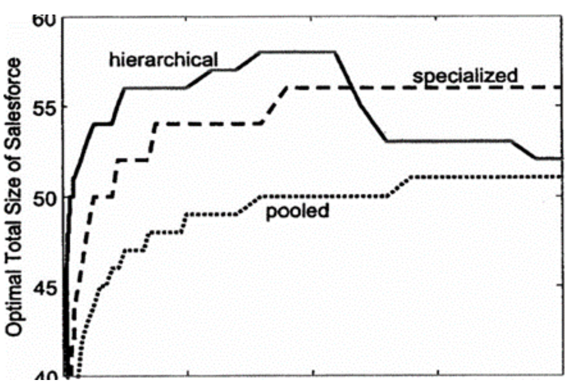
Compensation Rate, d ($/day)

Fig. 5. Optimal size of the salesforce as the cost of a salesperson, d, varies.

parameters ß and c. In each case, the presence of learning moderates the impact of changes in the other parameters.

6.3. Two products

In this section, we consider a firm with two distinct products and salesforces. We consider three options for managing these salesforces: (i) specialized; (ii) hierarchical; and (iii) pooled. Under the specialized structure, each salesforce has exclusive selling rights for one of the products and does not receive leads for the other. Therefore, the two products and their salesforces can be managed independently, as if there were only one product and one salesforce. Under the hierarchical structure we assume that each product has a primary salesforce, In Fig. 6 we plot the optimal staffing level as a function of the learning rate parameter n for the three salesforce structures. As in a traditional staffing problem, economies of scale in the pooled system lead to a smaller workforce than the specialized system. In addition, the optimal salesforce sizes of both the pooled and specialized systems increase with n, as suggested in the previous section's experiments with one product. thhierarchical sys-



Learning Rate (n)

The staffing pattern for the hierarchical system is due to the presence of experience-based learning in the model. When n is low, a salesperson with little experience is extremely unproductive, so experience gained by a salesperson must be focused on one product to maximize learning. In the specialized system, the learning is focused by design, but in the hierarchical system each salesperson receives overflow leads for their secondary products. To prevent this overflow, it is optimal when n is low to staff each salesforce at higher levels in the hierarchical system than in the specialized system. For high n, however, most salespeople reach the plateau of the learning curve for both primary and secondary products, and the staffng level for the hierarchical system is close to the level for the simple pooled system.

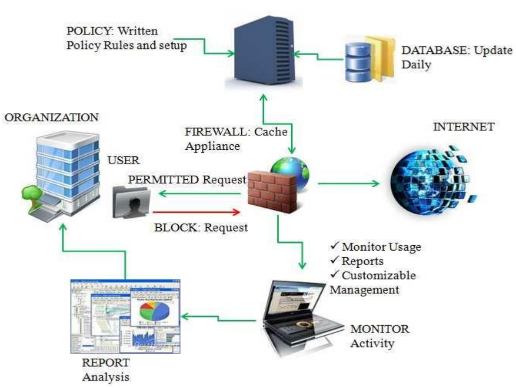
The dynamics described above also have an effect on pricing. In Fig. 7, we plot the optimal price as a function of the learning rates for all three systems. As the learning rate increases, the optimal price increases, because each salesperson becomes much more effective; increased learning leads

to a rise in the demand curve. We also see that the specialized system has higher prices than the pooled system because the specialized system has higher-skilled salespeople, producing a higher demand curve.

Finally, we examine which system is preferable, for a given value of n. Figures 8 and 9 compare the profitability of the three systems. For the lowest values of n, none of the systems are profitable. In this case, for a wide range of n the specialized system is more profitable because of that system's ability to focus its salespeople on a single product. O

VI. LIMITATIONS OF THE BASE PAPER

Figure shows how the enterprise filter can be physically connected with the organizations proxy servers, firewalls, cache engines or other Internet appliances. Logically new scheme or new schedule policy can be setup at the internet appliance or cache engine box. Then data collections scheduling database can be build to capture all the traffic that will conjunction with the Enterprise filter called the Master Database. This database can be organized and customize any new feature such as peer to peer applications such as MP3 downloading, movies online or unprofitable internet serving. Certain filtering or scheduling scheme can be managed to block or permit access to individual categories by user, group or time of day. An Internet filtering system would allow an administrator to monitor and controlling Internet access. Certain restrictions are setup on the system according to policy used within the organization. These restrictions could be the outright blocking of access to certain types of Internet sites, or the requirement of authentication, time of day controls or login access controls. The enterprise filter scheme could consistently refine its master database of sites using any artificial intelligence technology and Internet analysts such as adding the new sites filtering daily and the enterprise filter database could be refined to automatically downloads updates to the database every night to ensure that the network administrator keeping up with the rapid evolution of the Internet. This scheme could be enhanced from time to time and generate statistical data on the internet usage from or out of internet traffic in an organization.



VII. DESCRIPTION OF THE PROPOSED RESEARCH WORK

Survey on the literature review that focuses on modeling for the bandwidth management performances in an IP Based network then is compared and tabulated as in Table 2, Appendix A. Comparison has been made from the scope down information in table 1 which detailed out there is only three published papers on IP based network. Three different models have been used to implement bandwidth management. This model focuses and implemented on the different resources management such as to filter the routing traffics in the network, supporting the DS-TE in the MPLS networks and QoS controlled between end to end data aggregation. The three-implemented model used the ARMAX/GARCH model, MAM and a policy based model. A policy based model could be explore more in the next research where, it is an important plan or schedule need by the organizations. Different organization may need and want to implement a different policy based on their implemented network structure. This is why policies driven model can be enhanced further and new technique or algorithm can be produced based on this survey. Tabulated comparison in the table also shows that a different algorithm has been used in the different implemented model for the bandwidth management implementation. These algorithms are bandwidth allocations method, pre-emption algorithm and LSPs pre-emption algorithm and intserv-type of end to end point admission control. New techniques could be developed based on this algorithm method to improve the control and performance outcome.

VIII. CONCLUSIONS AND LIMITATIONS

This contradicts the conventional wisdom that the economy of scale provided by pooling reduces staffng requirements. We also show that, with learning, pooling using a hierarchical routing scheme is always preferred to pure pooling that randomly assigns leads to salespeople. Finally, in this paper, we use data collected from the salesforce of a large manufacturer, and fit the learning-curve and tenure-process parameters of the model to this data.

While this paper has contributed to the literature it is not without limitations. One extension of the current model would be to add a cost for lost leads to the profit function. Within the objective function of the model Equation (1), including such a cost is equivalent to including some additional revenue for each sale, revenue that does not depend upon the price. Therefore, a significant cost for each lost lead would increase the value of throughput, . In doing this one could draw upon the literature on the performance analysis of shared processors and polling systems. It would also be interesting to allow the salesperson to be a more active participant in the system, making both effort and pricing decisions, as in agency theoretic models. We have modeled the arrival process as exogenous, but in some environments, such as new or volatile markets in which the customer base is growing or changing quickly, the same salespeople are generating the leads and turning them into sales. It would be interesting to model how salespeople decide to allocate effort between generating leads and following leads up, within the context of a model of staffing with learning effects. We recognize that this is not an easy task because, among other complications, the service rates of the salespeople would be endogenous.

REVIEW

Focus Network Area	New Scheme /Algorithm	Enhanced Scheme /Algorithm	New Framework	New Modeled	Enhanc Mode l
IP Network [7],[8],[9]		1	1	1	
IPTV Network [10],			1		
Multi-hop/Hybrid /Mobile/ Wireless Network [2],[11],[12],[13],[14],[15],[16],[17][18],[19],[20],[21],[22],[23]	8	4		1	
Multimedia Wireless Network [24]		1			
Network Application & QoS [25],[26],[27],[28], [29]	3	1		1	
Network Protocol [30]	1				
Satellite Network [31],[32]		1		1	
System Performance [1],[33], [34],[35]	2	1			1
Total Knowledge Contributions	14	9	2	4	1

TABLE II
BANDWIDTH MANAGEMENT MODELING BASED ON AN IP NETWORK

Knowledge Area on Wired Network Model	Algorithm	Resource Management
1. Yongtao Wei; Jinkuan Wang; Cuirong Wang; Ling Cai [11]	ARMAX/GARCH throughput and packet loss	Bandwidth Allocation on Routing Traffic
2. Kotti, A.; Hamza, R.; Bouleimen, K [12]	MAM model an LSPs pre-emption algorithm	pre-emption algorithm and supporting DS-TE in MPLS networks
3. Ravindran, K.; Rabby, M.; Liu, X[13]	a policy-based model end-point admission control	intserv-type of end-to-end QoS control between data aggregation points

TABLE III
BANDWIDTH MANAGEMENT MODELING ON NETWORK APPLICATIONS

Knowledge Area on Network Applications	Model	Algorithm	Resource Application	Mathematical Equations
1. Rong OuYang; Hui Cao; Xianghua Xu; Jian Wan[29]	Bandwidth Allotment Model Of BTBM	A triggered dynamic mechanism	P2P – Bittorent	All bandwidth allotted to No. j BT connection is $B^{(ij)}_{alls} = B^{(ij)}_{strategy} + B^{(ij)}_{shutdown}$
2. Kashihara, S.; Tsurusawa, M[30]	Edge resource allocation	Call Admission Control (CAC)	IP Flow on bandwidth	$E_{ij} = F_{ij} + \frac{L_{ij} - \sum_{p=M}^{N} F_{pj}}{N - M + 1}$. (3)
3. Yongtao Wei; Jinkuan Wang; Cuirong Wang [31]	L-PREDEC	bandwidth allocation scheme	Bandwidth traffic	$\int_{x>0} \frac{1}{\sqrt{2\pi}\sigma_{err}} \exp(\frac{-x^2}{2\sigma_{err}^2}) dx$
4. Nen-Fu Huang; Hong-Yi Chang; Kuo-Shiang Hsu; Han-Chi Liu; Yuan-Wei Lin[32]	A linear approximation	The Next-Fit algorithm	Video streaming	Therefore we have $H(D) = \sum_{j=1}^{n-1} w_j + w_n < \sum_{j=1}^{n-1} w_j + w_1 < 2 * \sum_{j=1}^{n} w_j \leq 2 * \sum_{j=1}^{m} w_j^* = 2 * OPT(D)$ □
5 Xianqin Chen; Xiang Long; Xiaopeng Gao; Junjie Ma;[33]	System Model	QoS policy, netfilter packet processing	http ,ftp and bittorent	$P_{out} = \bigcup_{i=1,2,...,n} ts_i(\vartheta(<cHost_i, sHost_i, aProto_i>)) \subseteq P_{in}$

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