Modeling the Price-Reduction Effect in Mobile Telecommunications Traffic

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Abstract

As needs for telecommunications services diversify, an increasingly wide range of telecommunications services is becoming available in the market. Any subscriber can find a service to satisfy his/her telecommunication requirements and competition between providers to retain heavy users is increasing. Service price reductions are one retention strategy, although price reductions for one service can affect the individual-level usage for other services. Price reductions can also be imposed on a service provider by regulation. For these reasons, understanding how price reductions affect service usage is of growing importance to the telecommunications industry for purposes of pricing and tariff development. In this paper, we develop an individual-level usage model for telecommunications services and analyze the effects on usage of a price reduction. We apply the model to age-stratified aggregate traffic data for a Korean mobile telecommunication service provider. Finally, we develop a model to support a market segmentation and price reduction strategy.

1. Introduction

As needs for telecommunications services diversify, an increasingly wide range of telecommunications services is becoming available in the market. Any subscriber can find a service to satisfy his/her telecommunication requirements. Usage data for various telecommunications services reveal that subscribers' communication expenses are rapidly increasing. There are also now examples of a lack of consumer demand resulting in a service being withdrawn from the market, as was the case with services such as CT-2 (Cordless Telephone 2nd Generation) and Iridium. In other words, competition in the telecommunications industry has evolved from a state of competition among providers of the same service to one where services must compete with other types of services. Because of this change in the competitive environment, the marketing strategy of service providers has shifted from an emphasis on recruiting new subscribers to one on retaining existing heavy subscribers. In fact, the retention of heavy users has been the competitive mainstay of many telecommunications service providers. One strategy for maintaining these users is price reductions. Prices for a service vary by the tariff to which an individual subscribes. Price reductions for an advanced telecommunications service could easily erode the market for previously existing services, decreasing their traffic and revenue. Thus service providers stand to benefit from developing price structures and tariffs that take into account telecommunications usage behavior. In particular, pricing should be based on an analysis of individual-level traffic, the effects of service price reductions on that traffic, and consumer service requirements.

Brand [1] concluded that the structure of the emerging world information economy is being determined by traffic rather than by policy. A current traffic-related issue of interest in the telecommunication industry is the distribution of network traffic among telecommunication services [2]. In the next few years, the demand for telecommunications traffic data is likely to be at the local level. For individual service providers, for example, traffic data is critical to the development of pricing strategy, decisions about market segmentation, and the launch of new services. In the Korean telecommunications market, price reductions have occurred in response to demands by consumer groups. Service providers have also introduced new low-priced tariffs to attract price-sensitive customers. Furthermore, the government is likely to regulate the prices charged by service providers having significant market power. So service providers may choose to reduce prices for competitive reasons or may have price reductions forced on them.

Ideally, when making decisions about price reductions in this quickly evolving industry, advanced service providers would know the price elasticities of demand. By definition, however, advanced services do not have a long market history. With an advanced service, there are likely to have been few price reductions. Moreover, there may not exist enough individual traffic data to estimate those elasticities. In these cases, it would not be possible to estimate price elasticities using typical dynamic pricing models [3, 4]. After all, they are used to determine the price reduction of their various tariffs without knowing the price elasticities of tariffs.

Telecommunications traffic has been well studied. Some of this research was conducted using simulation to study the regulation of service and the operation of networks [5, 6] or queueing theory [7]. Jain, Muller and Vilcassim [8] provided a theoretical explanation for the pricing patterns for cellular handsets and phone calls using a game theoretic framework. Studies of traffic forecasting and price elasticities [9-15] analyzed international telecommunication traffic volume with respect to economic variables. Because these studies focused on aggregate traffic data, as opposed to individual-level data, they cannot explain the usage behavior of individuals. Squire [16] and Rohlfs [17] studied the implications of pricing telecommunications services based on demand. Mitchell [18] and Park et al. [19] estimated the price elasticities for local telephone calls. These models also have difficulties in applications at the individual level. In fact, there exist few methodologies and statistical models for individual-level telecommunications usage data. Even if methodologies did exist, it is difficult to pool individual-level usage data across providers because it is proprietary. Thus, each service provider can analyze only its own data.

In response to an ever more complex and competitive environment, telecommunications service providers have developed a variety of tariffs to address the needs of their subscribers. Telecommunications charges generally differ by service provider, service, and tariff. A price reduction for any particular service can affect individual usage for every other service available in the market. This environment calls for the development of a model to analyze individual usage data for a service provider. In particular, we focus on describing how subscribers respond to price reductions in advanced services where there may not exist sufficient data for the application of dynamic pricing models. In this paper, we develop an individual-level telecommunications service usage model, analyze the effect on usage of a price reduction, and develop strategy for market segmentation. The model could be used either by a service provider developing a pricing strategy or by a regulatory agency considering a mandated price reduction. In section 2, an individual-level usage model is developed. The model is then expanded to take into account the effect of a price reduction. Finally, we propose a method to determine a price reduction strategy for a segmented market in a loss minimization framework. In section 3, we apply the proposed model to age-stratified aggregate traffic data for a Korean mobile telecommunications service provider. Finally, section 4 presents a discussion of model limitations and directions for future research.

2. Individual-level usage model

The analysis of a service provider's individual-level usage data is very important to the development of a pricing strategy. A model of individual-level usage should incorporate the utility an individual obtains by using telecommunications services. The model should also incorporate the idea that when an individual uses many different telecommunications services, a price reduction in an advanced service is likely to affect his/her utility. In this section, we present such a model for telecommunications services.

2.1 Utility-maximizing usage model

Given the definition of a utility function and individual constraints, we derive the utility-maximizing usage level. An individual-level usage model can then be derived by combining the optimal usage with error correction behavior. In this model, all subscribers use both fixed telephone service (FPS) and mobile phone service (MPS). We define the FPS usage level of subscriber i in time period t as f_{it} and the MPS usage level of subscriber i in period as m_{it}. Throughout this paper, we define one unit of traffic volume as 10 seconds of service usage. Given the subscription tariffs for each of the two services, the subscriber pays a base FPS charge of B_f, a FPS usage charge of P_f per unit, an MPS base charge of B_m, and an MPS usage charge of P_m per unit.

We assume that an individual chooses a communication service and a level of usage to maximize his/her utility subject to a constraint, and define the utility in period t as:

$$U(f_{it}, m_{it}) \propto f_{it}^{\alpha} \cdot m_{it}^{\beta}. \tag{1}$$

This assumption of a Cobb-Douglas utility function form is reasonable because while the functional characteristics of FPS and MPS are similar, they are neither perfect complements nor perfect substitutes.

Subscribers to telecommunications services face various constraints. In this model, an individual has an upper limit (M) on telecommunications expenditures per time period so that $B_f + B_m + P_f \cdot f_{it} + P_m \cdot m_{it} \le M$. This is generally known as a budget constraint, and it may mean that the price of one service affects usage for other services [20]. In addition to maximizing utility, individuals generally prefer to pay the same amount in the current time period as they did in the previous time period so that $B_f + B_m + P_f \cdot f_{it} + P_m \cdot m_{it} \cong B_f + B_m + P_f \cdot f_{it-1} + P_m \cdot m_{it-1}$. Equation 2 represents the utility maximization problem given these two constraints.

$$\begin{aligned} &\max_{f_{it}, m_{it}} f_{it}^{\alpha} \cdot m_{it}^{\beta} \\ &s.t \quad B_f + B_m + P_f \cdot f_{it} + P_m \cdot m_{it} \le M \\ &\qquad B_f + B_m + P_f \cdot f_{it} + P_m \cdot m_{it} \\ &\qquad -(B_f + B_m + P_f \cdot f_{it-1} + P_m \cdot m_{it-1}) = 0 \\ &\qquad f_{it}, m_{it} \ge 0 \end{aligned} \tag{2}$$

Applying the Lagrangian method to (2), we derive the optimal usage level for FPS and MPS (f_{it}^{*} and m_{it}^{*}, respectively) at time t as shown in equation 3.

$$\begin{aligned} f_{it}^{*} &= \frac{\alpha}{\alpha+\beta} \cdot \frac{P_f \cdot f_{it-1} + P_m \cdot m_{it-1}}{P_f} \\ &(= \frac{\alpha}{\alpha+\beta} \cdot \frac{M - B_f - B_m}{P_f}), \\ m_{it}^{*} &= \frac{\beta}{\alpha+\beta} \cdot \frac{P_f \cdot f_{it-1} + P_m \cdot m_{it-1}}{P_m} \\ &(= \frac{\beta}{\alpha+\beta} \cdot \frac{M - B_f - B_m}{P_m}) \end{aligned} \quad (3)$$

The optimality condition from equation 3 is $P_f \cdot f_{it-1} + P_m \cdot m_{it-1} = M - B_f - B_m$. Larger values of α mean that FPS contributes more to utility, so as α increases, the FPS traffic volume increases and the MPS traffic volume decreases. And as would be expected, for either service, more expensive usage charges translate to less traffic volume.

While the solution to equation 3 maximizes an individual's utility, individuals may not be able to achieve exact optimal usage. This is because subscribers do not know, at any point in the current time period, their usage up to that point. After receiving a bill for period $t-1$, a subscriber would like to correct in time period t any violations of the condition $P_f \cdot f_{it-1} + P_m \cdot m_{it-1} = M - B_f - B_m$. Many studies have incorporated such a lagged variable when modeling demand [21-23]. Equation 4 represents the model when we include this error correcting behavior. In this model, the usage in the current time period is explained by its lagged value using an AR(1) process.

$$\begin{aligned} \begin{pmatrix} f_{it} \\ m_{it} \end{pmatrix} &= \begin{pmatrix} f_{it}^{*} \\ m_{it}^{*} \end{pmatrix} + \begin{pmatrix} \frac{a}{P_f} \\ \frac{b}{P_f} \end{pmatrix} \\ &\cdot \left(B_f + B_m + P_f \cdot f_{it-1} + P_m \cdot m_{it-1} - M\right) \\ &= \begin{pmatrix} f_{it}^{*} \\ m_{it}^{*} \end{pmatrix} + \begin{pmatrix} a \\ b \end{pmatrix} \\ &\cdot \left[\begin{pmatrix} 1, & \frac{P_m}{P_f} \end{pmatrix} \begin{pmatrix} f_{it-1} \\ m_{it-1} \end{pmatrix} - \frac{M - B_f - B_m}{P_f}\right] \end{aligned} \quad (4)$$

The parameters a and b in equation 4 represent the error correction behavior. If individuals are sensitive to expenditures in the previous period, these parameters have a large negative value. Note that equation 4 indicates that if an individual exactly achieves optimal usage, his/her traffic will be constant.

2.2 Usage model following a price reduction

In this section, we incorporate into the model the effects of a service price reduction for the advanced service, MPS, on usage of both MPS and FPS. Because telecommunications service providers must recover large capital investments and prepare for the next generation of services, price reductions generally occur infrequently (unlike with consumption goods). Providers would like to predict changes in traffic volume following a price reduction because such changes directly affect their revenues.

We assume the base charge is reduced to B_m' and the usage charge is reduced to P_m'. Applying the Lagrangian method, as before, to the utility maximization problem resulting with these new lower MPS charges, we obtain optimal solutions for FPS and MPS traffic volume in time period t, f_{it}^{**}

and m_{it}^{**}, with the new lower prices. The same optimality condition holds here as does in the previous case, namely: $P_f \cdot f_{it-1} + P_m^{'} \cdot m_{it-1} = M - B_f - B_m^{'}$. Equation 5 represents the model that incorporates error correction after an MPS price reduction. In this case also, the parameters a and b represent error correction behavior.

$$\begin{aligned}
\begin{pmatrix} f_{it} \\ m_{it} \end{pmatrix} &= \begin{pmatrix} f_{it}^{**} \\ m_{it}^{**} \end{pmatrix} + \begin{pmatrix} \dfrac{a}{P_f} \\ \dfrac{b}{P_f} \end{pmatrix} \\
&\cdot \left(B_f + B_m^{'} + P_f \cdot f_{it-1} + P_m^{'} \cdot m_{it-1} - M \right) \qquad (5) \\
&= \begin{pmatrix} f_{it}^{**} \\ m_{it}^{**} \end{pmatrix} + \begin{pmatrix} a \\ b \end{pmatrix} \\
&\cdot \left[\begin{pmatrix} 1, & \dfrac{P_m^{'}}{P_f} \end{pmatrix} \begin{pmatrix} f_{it-1} \\ m_{it-1} \end{pmatrix} - \frac{M - B_f - B_m^{'}}{P_f} \right]
\end{aligned}$$

Using the differences between the optimal solutions before and after the MPS price reduction, we can specify a model that estimates the optimal usage both before and after the reduction. In equation 6, the dummy variable d = 0 before the MPS price reduction and 1 after.

$$\begin{pmatrix} f_{it} \\ m_{it} \end{pmatrix} = \begin{pmatrix} f_{it}^{*} + (f_{it}^{**} - f_{it}^{*}) \cdot d \\ m_{it}^{*} + (m_{it}^{**} - m_{it}^{*}) \cdot d \end{pmatrix} + \begin{pmatrix} a \\ b \end{pmatrix} \cdot \left[\begin{matrix} \begin{pmatrix} 1, & \dfrac{P_m}{P_f} + (\dfrac{P_m^{'} - P_m}{P_f}) \cdot d \end{pmatrix} \begin{pmatrix} f_{it-1} \\ m_{it-1} \end{pmatrix} \\ -(\dfrac{M - B_f - B_m}{P_f} + (\dfrac{B_m - B_m^{'}}{P_f}) \cdot d) \end{matrix} \right] \qquad (6)$$

2.3 Individual-level usage model for a service

FPS has a long service history relative to that of MPS, and individual-level FPS usage volume has stabilized to a greater degree than has that of MPS. When a service provider does not have traffic data for both FPS and MPS, or when it is reasonable to assume that the FPS traffic volume is stable over a relatively short period, we can define the FPS traffic volume for subscriber i as constant ($f_{it} = \overline{f}_i$). Equation 7 describes the MPS traffic volume after an MPS price reduction under this assumption.

$$\begin{aligned}
m_{it} &= m_{it}^{*} + (m_{it}^{**} - m_{it}^{*}) \cdot d \\
&+ b \cdot [\overline{f}_i + (\frac{P_m}{P_f} + (\frac{P_m^{'} - P_m}{P_f}) \cdot d) \cdot m_{it-1} \\
&- (\frac{M - B_f - B_m}{P_f} + (\frac{B_m - B_m^{'}}{P_f}) \cdot d)] \\
&= b_1 + b_2 \cdot d + (b_3 + b_4 \cdot d) \cdot m_{it-1}
\end{aligned}$$

where

$$\begin{aligned}
b_1 &= m_{it}^{*} + b(\overline{f}_i - \frac{M - B_f - B_m}{P_f}), \\
b_2 &= (m_{it}^{**} - m_{it}^{*}) - b \cdot (\frac{B_m - B_m^{'}}{P_f}), \\
b_3 &= b \cdot \frac{P_m}{P_f},\ b_4 = b \cdot (\frac{P_m^{'} - P_m}{P_f}) \qquad (7)
\end{aligned}$$

The MPS model in equation 7 can produce eight different behaviors, depending on whether the constant and AR(1) process parameter change after the price reduction. We assume the AR(1) process in equation 7 is stationary. It is well known that when the AR(1) process parameter has a large positive value, neighboring observations in the series are similar (i.e., the consumer is insensitive to expenditures in the previous period). When the parameter has a large negative value, the series tends to oscillate (i.e., the consumer is sensitive to previous expenditures). Because the usage in (7) follows a stationary AR(1) process, we know the mean usage before and after a price reduction are $\frac{b_1}{1-b_3}$ and $\frac{b_1+b_2}{1-(b_3+b_4)}$, respectively. We can then select the model from among the eight alternatives for which the P-values of all estimated parameters (b_1, b_2, b_3, b_4) are significant and the model's Mean Square Error (MSE) has the minimum value. Also, we should consider the specification errors of the estimated equation [24]. Table 1 describes the eight possible combinations of behaviors before and after a price reduction. These combinations fall into two categories. In the first, traffic before a price reduction is constant ($m_{it} = b_1$). In the second, traffic before a reduction follows an AR(1) process ($m_{it} = b_1 + b_3 \cdot m_{it-1}$). For both categories, there are four possible behaviors following a price reduction. The first is that there is no change in traffic. The second is that there is an instant increase in the traffic volume ($b_2 > 0$). The third is that there is a change in the AR(1) traffic process parameter value ($b_4 > 0$). This parameter may indicate a new sensitivity to price following a price reduction. The fourth is that both the second and third cases are true, and both b_2 and b_4 are significant in the model. In this case, the change in mean traffic volume is the difference between $\frac{b_1}{1-b_3}$ and $\frac{b_1+b_2}{1-(b_3+b_4)}$.

[Table 1]

2.4 Subscriber segmentation and price reduction strategy

Telecommunications service providers are developing increasingly complex tariff structures for their services. The purpose of these tariffs is to vary the pricing of telecommunications services to attract and retain as many subscribers as possible. Tariffs may vary for different segments of the population. In Korea, for example, service providers developed several tariffs based on specific age groups, e.g., teenagers and the elderly. In the past, tariffs and price reductions have not been based on an analysis of usage behavior. We believe that the development of new tariffs should take into account both the structure of existing tariffs and subscriber usage behavior. To this end, it would be helpful to group together subscribers who respond in the same way to price reductions, and then to target price reductions to segments in a way that maximizes profit (or minimizes loss).

As described earlier, price reductions can either result from a decision by a service provider or can be imposed on a service provider. For example, in Korea there was a movement among consumer groups to reduce the price of MPS. These groups named a target nominal reduction rate to the government and service providers. In a situation like this, service providers may have some flexibility as to how they achieve this reduction. We formulate a simplified assignment problem that incorporates subscriber responses to reductions to develop a price reduction strategy that minimizes loss. If there is no price reduction, the loss would be zero. A price reduction that resulted in higher revenues due to increased usage would produce a negative loss. The model formulated here could apply, for example, if a provider were considering a price reduction as a competitive strategy. In this case, the provider might consider making a reduction if the negative impact on revenue was not significant. While we describe a particular problem, the framework is general enough to incorporate other objective functions or constraints. We assume that the market is segmented, and that we can assign a price reduction to some segments and not to others. In other words, different tariffs can be developed for different market segments. In this case, the market will experience an average, or nominal rate of reduction. We impose two constraints. The first is that the decrease in the service provider's total revenue cannot exceed y%. The second is that the nominal price reduction rate be at least z%. The assignment problem for the k-th price reduction is then formulated as in equation 8, which includes an assumption that subscribers do not move between groups following a price reduction. We define $\bar{M}^s_{(k-1,k)}$ as the average monthly traffic volume for an individual in group s after the k-1st price reduction, and n_s as the numbers of subscribers in group s with a total of S groups. The decision variable x_s = 1 if the price for group s is to be reduced, and 0 otherwise. B_m and B'_m are the base charges before and after the price reduction, respectively. Similarly, P_m and P'_m represent the usage charges before and after the price reduction, respectively. This problem can be solved using a spreadsheet solution solver or an integer programming tool.

$$\min_{x_1,\ldots,x_s} Loss = \sum_{s=1}^{S} x_s \cdot n_s \cdot (B_m - B'_m + P_m \cdot \bar{M}^s_{(k-1,k)} - P'_m \cdot \bar{M}^s_{(k,k+1)})$$

$$s.t \quad 1 - \sum_{s=1}^{S} [x_s \cdot \frac{B'_m + P'_m \cdot \bar{M}^s_{(k,k+1)}}{B_m + P_m \cdot \bar{M}^s_{(k-1,k)}} + (1 - x_s)] \cdot \frac{n_s}{\sum_{s=1}^{S} n_s} \leq y\%$$

$$1 - \sum_{s=1}^{S} [\frac{P'_m}{P_m} \cdot x_s + (1 - x_s)] \cdot \frac{1}{S} \geq z\%$$

$$x_s = 0 , 1 \tag{8}$$

3. Applications

In this section, we apply the model developed in section 2.3 to age-stratified aggregate traffic data for a Korean mobile service provider. These data represent the monthly average traffic volume for individuals including 4 different tariffs and 13 age groups (for a total of 52 groups) from August 1999 to March 2001. These 4 tariffs represent a standard tariff, and tariffs developed for heavy users, couples, and youths. A single price reduction occurred in the Korean mobile phone market in that period, in April 2000. The data set represents approximately 5,840,000 individuals, each assigned to an age group. We define the MPS usage level for one subscriber in age group g in period t as m_t^g.

3.1 Application of the forecasting model

The application of the model to these data revealed that traffic did not change following the price reduction in 17 out of the 52 groups. The parameter representing price sensitivity to the reduction (b_4) was significant in only 29 groups. In the 6 remaining groups, traffic volume increased instantly, resulting in a significant value for b_2. In the 17 groups with no traffic change, the parameter representing the effect of AR(1) traffic before the price reduction (b_3) had 0 or positive value (>0). This indicates that these groups are insensitive to the price reduction. In the estimated results for all 52 groups, there is no case where both parameter b_2 and b_4 are significant, thus eliminating the two of eight cases where $m_t^g = b_1 + b_2 + b_4 \cdot m_{t-1}^g$ and $m_t^g = b_1 + b_2 + (b_3 + b_4) \cdot m_{t-1}^g$ in Table 1.

Figure 1 presents observed and fitted plots for 6 of the 52 groups analyzed. Each plot corresponds to a single age group and represents one of eight cases described earlier. The vertical line on each plot indicates the time of the price reduction, April 2000. The horizontal axis represents time period and the vertical axis represents monthly individual-level traffic volume. Because calendar months differ by the number of holidays, Sundays, Saturdays and weekdays, a monthly-adjusted index was used for model estimation.

[Fig. 1]

In figure 1, plots a and b correspond to age groups that exhibited no change in traffic following the price reduction. The remaining plots correspond to groups that did respond to the price reduction. In several of these groups, both parameters b_3 and b_4 were found to be significant, as in plot f.

Table 2 presents the results of the model application for one tariff with 13 age groups. Because the available data were proprietary to the service provider, the estimated values of parameters b_1 and b_2 are not reported here.

[Table 2]

These results show that consumers in this tariff exhibited only four of the eight possible behaviors. Note that b_3 has a negative value (<0) for groups 6 to 13. A possible interpretation of this is that the subscribers in these groups are sensitive to previous expenditures and this sensitivity increases with age. The parameter representing a price sensitivity effect following the price reduction (b_4) has a positive value for the groups under age 15 and over age 40, perhaps indicating that subscribers in these groups become slightly insensitive to price following a reduction. There was no change in traffic volume in groups 4 and 5. For groups with individuals from ages 25 to 39, the traffic volume increased instantly following the price reduction, as indicated by the significant value for b_2.

Figure 2 shows the log spectral density function depicting the change in the AR(1) traffic process parameter following the price reduction ($b_3 \rightarrow b_3 + b_4$). In these graphs, the horizontal axis represents frequency and the vertical axis represents log-spectral density. Figure 2a represents group 10, where the AR(1) parameter increased from -0.495 to (-0.495+0.140) = -0.345. Figure 2b represents a group where the AR(1) parameter increased from 0.211 to 0.264. (This group is not included in the tariff represented in table 2).

[Fig. 2]

The dotted line corresponds to the log spectral density function before the price reduction and the solid line to that after the price reduction. In both groups, the spectrum of these traffic series shifted to lower frequencies after the reduction. This implies that subscribers of these groups became insensitive to previous expenditures.

3.2 Application of the price reduction strategy model

In this section, we apply the proposed price reduction strategy method to choosing which segments of the market should be targeted with a reduction to minimize revenue loss. Following the price reduction in April 2000 in the Korean mobile telecommunications market, further reductions occurred in January 2002 and January 2003. Service providers were responding to demands of consumer groups. We had hoped to develop and apply our methods to the next price reduction, but were unable to obtain individual–level usage data corresponding to a second price reduction. We instead used the results presented in table 2, and assume that we can decide for each age group whether or not to reduce prices for subscribers in that group. Some countries may not permit differential pricing by age. In most cases, however, a market can be segmented by some attribute, and the method proposed here would be applicable to targeting price reductions by that attribute. The constraints for this example are that the resulting revenue decrease not exceed 2.5% and that the total nominal rate of the price reduction be at least 5%. Table 3 shows the assumed base values for telecommunication charges used. In this example, the nominal reduction rate for the base charge is $11(=\frac{₩27,000-₩24,000}{₩27,000})\%$ and for the usage charge is $10(=\frac{₩30-₩27}{₩30})\%$.

[Table 3]

The model determined that the optimal target groups for the price reduction are 1, 2, 3, 4, 11, 12 and 13. The results in Table 2 show that, with the exception of group 4, these are all groups that are expected to respond to a price reduction by increasing usage, thereby offsetting potential revenue losses. Even though the model predicted that the usage of group 4 would not change following the price reduction, the loss function coefficients for this group were smaller than those of the other non-targeted groups. For the same reason, group 10 was not included even though it appears very similar to group 11. The expected revenue loss to the service provider from this tariff is ₩19.7 (hundred million won/month), resulting in a nominal reduction rate of 5.4%. If the price were reduced as in Table 3 for all thirteen groups, the expected revenue loss from this tariff would be ₩148.3 (hundred million won/month), resulting in a nominal reduction rate of 10%.

4. Discussion and conclusions

In response to growing and diversifying needs, an ever-wider selection of telecommunication services is available to consumers whose communications expenses are rapidly increasing. For service providers, the emphasis of marketing strategy has shifted from recruiting new subscribers to retaining heavy subscribers. Price reductions may occur in this market in response to government regulation, calls by consumer groups to lower prices, the launch of advanced services, or the introduction of new tariffs. While price reductions may help to retain heavy users, reductions for advanced telecommunications services can easily erode the market for older telecommunications services, resulting in revenue loss. For this reason, pricing decisions should take into account how subscribers may respond to price reductions. When making such decisions for advanced services, however, there may not exist a history of price reductions. Furthermore, the available age-stratified aggregate traffic data may be insufficient to estimate the price elasticities making the typical dynamic pricing models of little use.

In this paper, we developed an individual-level usage model for telecommunication services and analyzed the effect of a price reduction on that usage. After defining a utility function and individual-level constraints, we derived the utility maximizing usage volume. Next, an individual-level usage model was developed for telecommunications services that incorporates this optimal traffic volume and error correction behavior. We used this model to look at usage following a price reduction and identified eight possible behavioral responses to the reduction. Finally, a method was proposed for a market segment-based price reduction strategy in a loss minimization framework. The usage model and the market segmentation model were applied to age-stratified aggregate traffic data for a Korean mobile telecommunications service provider. This time period covered by this data set included one price reduction.

The model was applied to data representing individual-level usage by 52 groups defined by age and tariff. Among these groups, 17 exhibited no change in volume following the price reduction. The parameter representing price-sensitivity following the price reduction (b_4) was significant in only 29 groups. Traffic volume for the remaining 6 groups increased instantly, as represented by the significance of the parameter b_2. In the 17 groups exhibiting no traffic change, the effect of AR(1) traffic before the price reduction (b_3) was 0 or had a positive value (>0). A negative value for the parameter b_3 suggests that subscribers in that group were sensitive to the previous expenditures. The post-reduction price sensitivity parameter, b_4, had a positive value for several groups which suggests that subscribers in these groups became increasingly insensitive to prices after the reduction. Because data describing individual-level traffic following the second price reduction were not available, we were not able to validate the forecasting methods.

We then showed how a targeted price reduction strategy could help a service provider to achieve a total nominal price reduction in a way that minimizes negative impact on revenues. The strategy allows the provider to target reductions by market segment, where the segments in this example were defined by subscriber age. One goal of the strategy is to focus the price reduction on market segments that will respond to a price reduction by increasing use. In the application of this model, the best targeted reduction strategy resulted in a revenue loss of ₩19.7(hundred million won/month). An untargeted strategy would result in a revenue loss of ₩148.3(hundred million won/month).

There are some limitations to the modeling approach developed in this paper. The model described eight possible combinations of behaviors before and after a price reduction. There is the possibility that this does not capture all possible usage behaviors in response to marketing pricing models. Though the model we proposed incorporates two different services (FPS and MPS), we applied it only to MPS because we only had individual-level data for MPS. There now exist many new value-added services such as wireless internet service, SMS (Short Messages Service), and location-based service. The model developed in this paper could be extended for any of these various services. There are also many variations of the market segment-based price reduction strategy that should prove useful to service providers. For example, it may be the case that the size of the usage price reduction is a decision variable. We plan to explore these variations further in future analyses.

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Table 1: Changes in mean usage following a price reduction

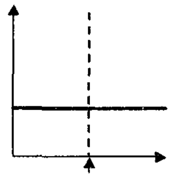
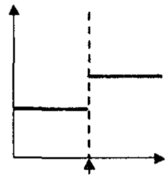
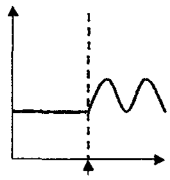
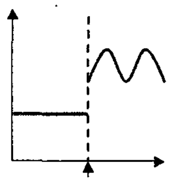
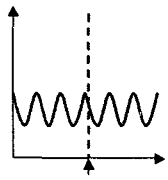
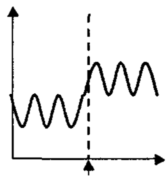
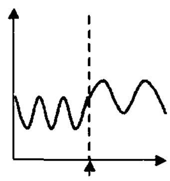
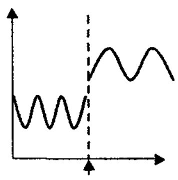
Usage (Before)	Usage (After)	Change pattern	Change in mean usage
$m_{it} = b_1$	$m_{it} = b_1$		0
	$m_{it} = b_1 + b_2$		b_2
	$m_{it} = b_1 + b_4 \cdot m_{it-1}$		$\frac{b_1}{1-b_4} - b_1$
	$m_{it} = b_1 + b_2 + b_4 \cdot m_{it-1}$		$\frac{b_1+b_2}{1-b_4} - b_1$
$m_{it} = b_1 + b_3 \cdot m_{it-1}$	$m_{it} = b_1 + b_3 \cdot m_{it-1}$		0
	$m_{it} = b_1 + b_2 + b_3 \cdot m_{it-1}$		$\frac{b_2}{1-b_3}$
	$m_{it} = b_1 + (b_3 + b_4) \cdot m_{it-1}$		$\frac{b_1}{1-(b_3+b_4)} - \frac{b_1}{1-b_3}$
	$m_{it} = b_1 + b_2 + (b_3 + b_4) \cdot m_{it-1}$		$\frac{b_1+b_2}{1-(b_3+b_4)} - \frac{b_1}{1-b_3}$

Table 2: Results of model application to data for one tariff

Index	Age group (years)	Estimated parameter values (**: 99% significant)				Change in average traffic volume (10 sec. Blocks)
		b_1	b_2	b_3	b_4	
1	Below 10	(**)			0.361(**)	475.3
2	10~12	(**)			0.184(**)	209.2
3	13~15	(**)			0.157(**)	171.9
4	16~19	(**)				0
5	20~24	(**)				0
6	25~29	(**)	(**)	-0.262(**)		82.5
7	30~34	(**)	(**)	-0.396(**)		77.9
8	35~39	(**)	(**)	-0.416(**)		72.5
9	40~44	(**)		-0.481(**)	0.118(**)	83.0
10	45~49	(**)		-0.495(**)	0.140(**)	90.5
11	50~54	(**)		-0.479(**)	0.140(**)	81.3
12	55~59	(**)		-0.492(**)	0.138(**)	70.3
13	Above 60	(**)		-0.500(**)	0.152(**)	75.0

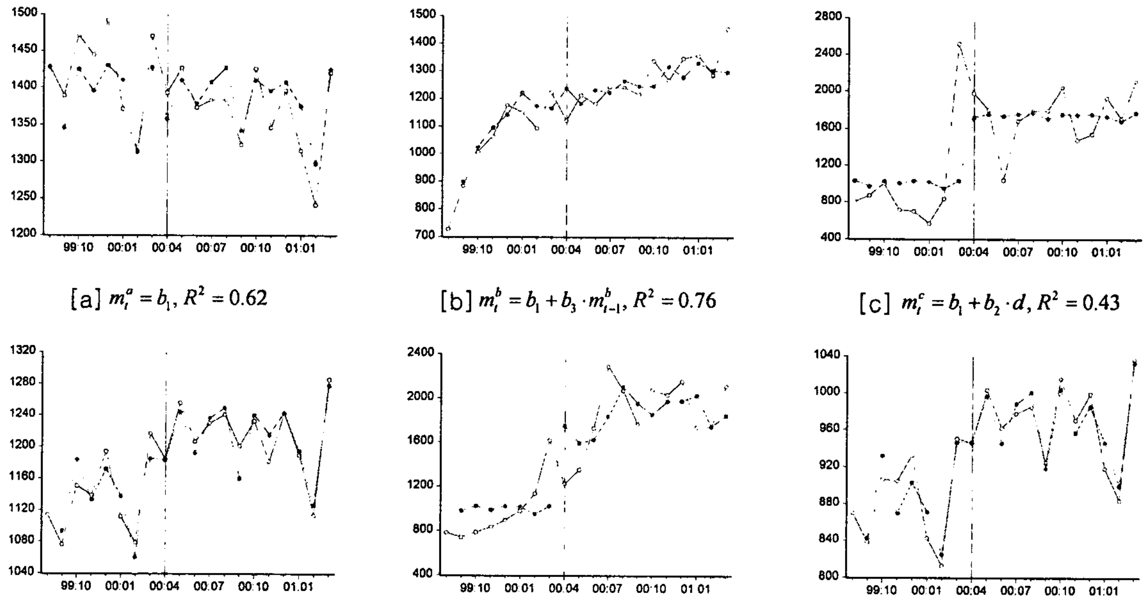
Table 3: Base values for the price reduction decision problem

Parameter		Value	
Base charge before reduction (B_m)		₩27,000	
Base charge after reduction ($B_m^{'}$)		₩24,000	
Usage charge before reduction (P_m)		₩30 (per 10 sec.)	
Usage charge after reduction ($P_m^{'}$)		₩27 (per 10 sec.)	
Number of subscribers by group			n_1 =152
n_2 =106	n_3 =147	n_4 =14,332	n_5 =164,008
n_6 =495,534	n_7 =643,074	n_8 =729,791	n_9 =713,063
n_{10} =466,142	n_{11} =284,707	n_{12} =168,565	n_{13} =146,292

Captions to Illustration

Fig. 1. Representative fitted plots of traffic volume for single age groups (-○-: Actual, -●-: Fitted)

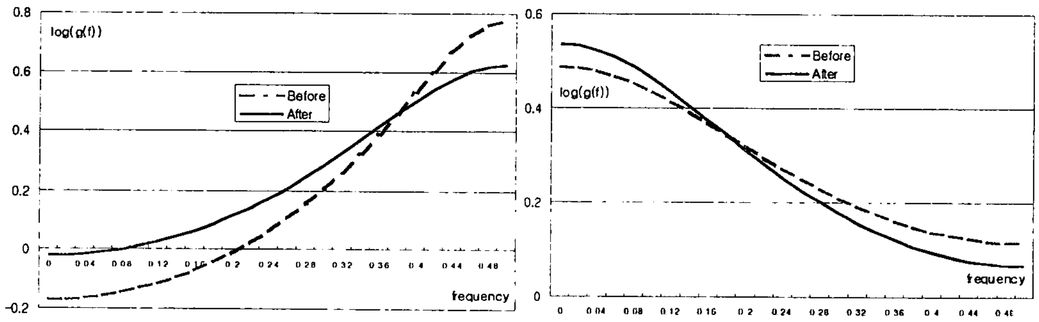
Fig. 2. Examples of log-spectral density functions



[a] $m_t^a = b_1, R^2 = 0.62$ [b] $m_t^b = b_1 + b_3 \cdot m_{t-1}^b, R^2 = 0.76$ [c] $m_t^c = b_1 + b_2 \cdot d, R^2 = 0.43$

[d] $m_t^d = b_1 + b_2 \cdot d + b_3 \cdot m_{t-1}^d, R^2 = 0.88$ [e] $m_t^e = b_1 + b_4 \cdot d \cdot m_{t-1}^e, R^2 = 0.80$ [f] $m_t^f = b_1 + (b_3 + b_4 \cdot d) \cdot m_{t-1}^f, R^2 = 0.91$

Fig. 1. Representative fitted plots of traffic volume for single age groups (-○-: Actual, -●-: Fitted)



[a] $b_3 = -0.495, b_4 = 0.140$ [b] $b_3 = 0.211, b_4 = 0.053$

Fig. 2. Examples of log-spectral density functions