Optimal Personalized Prepaid Cellular Plans

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***Abstract*—One new trending feature of Smartphones is the support for E-SIM (Embedded Subscriber Identification Module) cards. These allow the user to simultaneously subscribe to multiple cellular providers while also supporting at most one physical SIM (Subscriber Identification Module) card. This feature allows customers to easily switch between providers and is especially useful for those who use prepaid plans which are popular in developing countries. A customer may have multiple providers, and at any point in time choose the provider with the most cost effective data plan. This means that cellular providers, in addition to considering the more traditional churn where a consumer switches providers, must now also consider this soft-churn whereby the consumer dynamically switches between multiple plans from multiple providers. This means that data pricing for such consumers must now be more personalized in order to be competitive. We determine the optimal personalized prepaid plan for such users while providing a competitive advantage to the provider. We also provide examples to demonstrate its benefit. Numerical results corroborate that personalized over traditional pricing plans can improve the revenue of the provider.**

***Index Terms*—Pricing Plans, Prepaid Plans, Cellular Data Pricing, E-Sim**

I. Introduction

A significant number of papers have been written on customer churn in the Telecommunications industry. However this form of churn was mainly researched in the postpaid context which involve customers who pay for service in advance on a monthly basis. Such plans are common in developed countries. However, in developing countries, prepaid plans are far more popular. With these types of plans, a customer pays for services in advance and once exhausted they pay for an additional plan or "top-up" their present plan. For example, if we consider Latin American countries, we can see from Figure 1 that for all countries considered, the majority of customers were on prepaid plans [1]. This observation holds regardless of population size. Therefore, in these countries, revenue optimization must be more focused on prepaid plans rather than on postpaid plans and the associated churn.

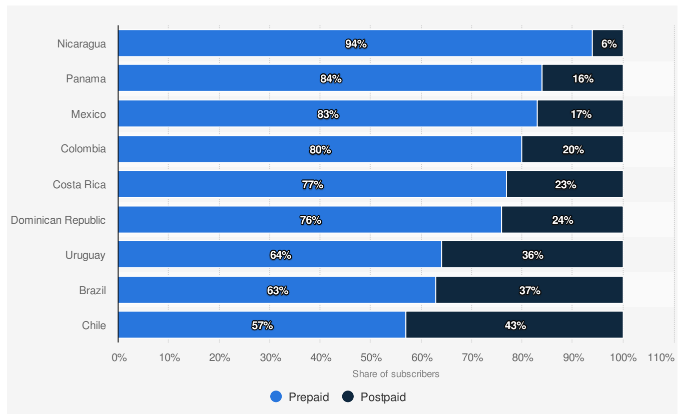

Fig. 1. Distribution of mobile subscribers in selected countries in Latin America in 2017, by contract type [1]

In countries with predominantly prepaid customers, many customers purchase SIM cards from multiple cellular providers. This fact is clear when one finds that the mobile penetration rate in some countries exceeds 100%. The main reason is that in-network calls tend to be cheaper (or free) when compared to calls made outside of the network of the caller.

Prepaid customers present unique challenges since they can cease their activity without notice and are not contractually bound to their provider. Churn can be classified into two types based on the initiator of the churn action: voluntary churn (customer-initiated) and involuntary churn (initiated by the provider) [2]. The management of customer churn is of great concern to global telecommunications providers and is particularly acute in mature markets. According to Ahn et. al. [3], the annual churn rate ranges from 20% to 40% for most global mobile telecommunications providers. In this paper we examine the behaviour of customers that switch from one provider to another with respect to both the physical SIM, where traditional churn occurs, and the E-SIM, where soft churn occurs.

The mobile industry has traditionally relied on a physical SIM card, which is a security element used in the authentication and identification of the subscriber before granting access to the mobile network [4]. Currently, roughly 15 billion devices are equipped with physical SIM cards. However, there are several limitations, including the fact that it occupies a large amount of space within the device, can be stolen, is easily damaged, and requires unnecessary maintenance and management [5].

With recent advances in wireless and storage technologies, the embedded SIM (E-SIM) has become a popular alternative and consists of a tamper resistant module soldered on the mobile phone and a software SIM downloadable over-the-air [4]. This type of SIM performs the same task as a traditional SIM and enables the secure changing of subscription identity and other subscription data. Its main advantage is that it is more flexible and convenient, allowing customers to access multiple providers simultaneously [6]. Therefore, a customer may choose between plans but they would need to have a SIM card for each provider. Note that this form of soft churn is different to the traditional churn typically discussed whereby a customer switches from one provider to another and only uses one provider at a time. Therefore, this introduces flexibility of customer choice, allowing for the potential to increase soft churn [6], as well as fiercer competition amongst providers. Therefore, to remain competitive, the E-SIM and soft churn should be accounted for and prepaid plans should become personalized.

II. Related Work and Contributions

Customer churn is extremely important to businesses since it has the potential to significantly impact their revenues. Predicting customer churn is a supervised classification problem, meaning that customers can either churn (churners), or not churn (non-churners) [7]. There are several factors that can contribute to customer switching behaviour. Chandha and Bhandari showed that factors such as network quality, tariffs, technology, advertising, rewards programs and other external factors may influence a customer's decision to switch their mobile services provider [8]. Similarly, Rajeswari and Ravilochanan found that churn was impacted by issues related to technology based services, network coverage, network speed and complaint resolution [9]. Furthermore, in Turkey, it was demonstrated in [10] that data usage, type of plan, and campaign awareness affected churn and customer retention.

Some authors have used number portability data to determine churn [11]. However, in situations where mobile portability was not applicable, studies by [12] and [13] showed that a period of time where the customer has not used their device, for e.g. incoming calls, can be used to determine churn. Prior research suggests that the reliance on local customer attributes for traditional churn prediction may be insufficient when considering that prepaid plans can be purchased and used anonymously. Thus, other attributes need to be investigated, such as data usage [7].

For providers to stay competitive, pricing plans need to be flexible. Generally there are two types of plans: static and dynamic. Static plans use predetermined rates for their base charge and customers' usage behaviour is not taken into account [14]. Dynamic plans determine optimal selling prices that can be easily and frequently adjusted [15]. Our paper expands on the dynamic approach where we will examine personalized pricing plans. Several studies [16]–[18] have shown that dynamic time-dependent pricing can be used for revenue optimization regarding Internet Service Providers (ISPs). This approach was found to increase the provider's revenue and users were able to achieve higher total utilities, when compared to the providers that used the baseline static pricing approach. Others [19] [20] examined personalized mobile strategies, where it was found that, compared to non-personalized targeting, personalized dynamic engagement-based targeting generated 101.84% more revenue [20].

Since E-SIMs are relatively new, there are presently no studies that investigate their effect on soft-churn, nor their impact in a prepaid environment. There has only been a prediction that churn is likely to increase due to the ability of the E-SIM to dynamically switch plans and providers [6].

In the next section we briefly review present pricing models for prepaid plans. We then describe our proposed approach to pricing under the assumption that the device has an E-SIM. We then provide an illustrative example to demonstrate the benefit of the proposed personalized plan approach. Finally we give a more realistic simulation example to again demonstrate benefits.

III. Traditional Prepaid Pricing Model

We consider customers who use cellular prepaid data plans in which the customer pays for a certain number of transfer data in Gigabytes (denoted by D) that must

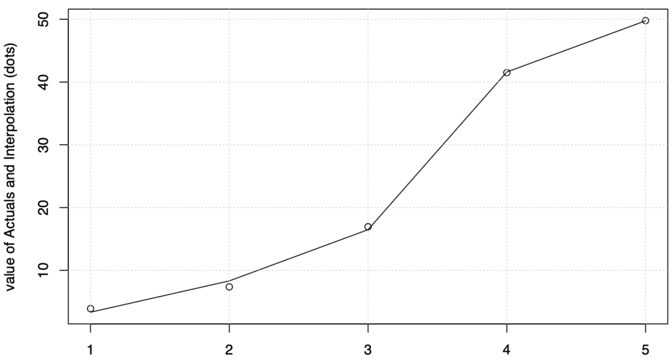

Fig. 2. Prices and Regression Estimates versus Plans

be used over a certain period of time in days (denoted by T). For example, they may purchase a data plan for 30GB of data to be used over a 30 day period.

Note that providers charge more for more data since this requires more resources to provide the data transfer. They also charge more for longer usage periods because maintaining the phone on their network requires resources even if not being used for data transfer. Lastly there is a fixed cost, γ, to setup the plan for the customer. Finally the provider makes some profit, and so the price of the plan will be given by $1 + \kappa$ times the cost where κ is the profit margin. So we represent the price P of the plan by

$$P = (1 + \kappa)(\alpha D + \beta T + \gamma) \tag{1}$$

where α is the cost to provide one GB of data and β is the cost to maintain the device on the network for one day.

We illustrate this model by applying it to prepaid prices for an actual provider. This provider has 5 different plans with varying data and time allowances. Using the above model, we used linear regression to determine estimates of the function parameters and obtained

$$P = 2.18 + 0.83D + 0.90T \tag{2}$$

This implies a fixed cost of \$2.18 with per GB and per day costs of \$0.83 and \$0.90 respectively. In Figure 2 we plot the actual prices and those computed using linear regression for the five plans to illustrate that the linear model fits well.

We repeated this process for a competitor of this provider. However this competitor's plans provided unlimited data but subject to a fair use policy. In this case one could consider the data used would be linearly proportional to the duration of the plan and hence one only needs to consider the dependence on T. For the plans of this provider we obtained

$$P = 2.32 + 1.87T \tag{3}$$

Therefore the fixed cost is \$2.32 while the per resource (GB or day) cost is \$1.87 compared to \$1.73 for the previous provider. This provider did have one plan with limited data at a cost of \$35.78. Although the previous provider did not have such a plan, the estimated cost using the linear regression model would have been \$31.54.

IV. Personalized Plans

In order to fully utilize the cost of the plan, the consumer must use all data and this must be done over the entire plan period. If the data is utilized before the allotted time, then the plan terminates, and so the provider saves on the resources for the remaining days. Similarly, if the customer does not use all data by the end of the allotted period then the provider saves on the resources that would have been required to transfer the unused data.

Suppose we know the rate of data usage (e.g., R GB per day) of a consumer. This can be computed based on historical data. Furthermore, suppose that the customer knows how long they wish to use the plan, $\hat{T}$. We can compute the optimal price for the customer (i.e. the price that would result in full data usage at the end of $\hat{T}$. This would be given by

$$P = \alpha R\hat{T} + \beta\hat{T} + \gamma$$

Note that such personalized plans are always optimal for the customer at the expense of the provider. If, for example, the purchased plan provided $D > R\hat{T}$ data, then the customer would have had to pay an additional amount of $\alpha(D - R\tilde{T}$ for the extra data that was not used. If the purchased plan provided $D < R\hat{T}$ then the customer would run out of data before the time limit, and so would pay $\beta(\hat{T} - D/R)$ for time that was not used. However, since such pricing benefits the customer, then any provider not using such a scheme stands to lose the customer. In this way, a provider using such a pricing plan will attract more customers and can achieve greater total revenue.

V. Soft Churn with Multiple Providers

In the previous section we showed that the provider who offers customers personalized plans, make a lower profit per customer, but will attract more customers. In order to better understand the dynamics, let us first consider a scenario with two providers. We assume that one provider offers traditional plans while the second provider offers personalized plans. We assume that the resource costs (cost to transfer a GB and cost to maintain a device for a day) are the same for both but that the profit margins are κ_t and κ_p respectively. Consider a single customer and assume that they typically use $\tilde{D} < D$ out of their purchased plan before running out of time. The profit for the traditional provider is given by

$$F_t = (1+\kappa_t)(\alpha D + \beta T + \gamma) - (\alpha \tilde{D} + \beta T + \gamma) \quad (4)$$

while for the personalized plan the profit is

$$F_p = \kappa_p(\alpha \tilde{D} + \beta T + \gamma). \quad (5)$$

One can argue that the traditional provider can lower their profit margin in order to be competitive with the personalized plan provider and avoid losing customers. However, even if $\kappa_t = 0$, there is still a profit made by the traditional provider. For the personalized plan provider, the profit goes to zero as κ_p goes to zero. Therefore, our proposed approach is to increase κ_p while ensuring that $F_p < F_t$. In this way, customers will still migrate to the personalized plan provider (because they benefit more) and this provider will continue to make an acceptable profit.

We achieve this goal as follows. Let $\tilde{D} \le D$ denote the data used by the customer and let $\tilde{T} \le T$ denote the time used on the plan. Note that either $\tilde{T} = T$ or $\tilde{D} = D$. We use the following personalized price for the customer.

$$P_p = (1+\kappa_p)(\alpha \tilde{D} + \beta \tilde{T}) + \gamma \quad (6)$$

Now note that the minimum price for the traditional approach is

$$P_t(\kappa_t = 0) = \alpha D + \beta T + \gamma \quad (7)$$

which occurs when $\kappa_t = 0$. Let us consider the case where $\tilde{T} = T$. We can show that if $\kappa_p < (D - \tilde{D})/\tilde{D}$ then $P_t(\kappa_t = 0) > P_d$ and hence this customer will switch to the personalized plan, otherwise, they benefit more with the traditional plan. Note that these are the customers who are far from utilizing their full data allocation (i.e. the ones who can benefit more from a personalized plan) and these are the customers who should be attracted. In the case of $\tilde{D} = D$ we similarly have that if $\kappa_p < (T - \tilde{T})/\tilde{T}$ then $P_t(\kappa_t = 0) > P_d$ and these customers will also migrate to a personalized plan. In conclusion, if a provider uses personalized plans, they can attract those users who do not use the full resources available with their plan and profit from such users. The traditional provider will continue to keep the higher usage users but those are the users that provide less profit.

VI. Illustrative Example

Let us illustrate the benefit of the approach with an illustrative example. Let us assume that we have customer usage statistics from a traditional provider and consider the set of users that run out of time before using all of their data. Let $f(x)$ denote the probability that a user consumes a fraction x of their data on expiration of their plan. We consider the extreme case in which $\kappa_t = 0$ and so, the traditional provider reduces their profit margin to compete as best as they could with the personalized plan provider. When the personalized plan provider enters the market we assume that they capture all customers for which the personalized plan is cheaper than the traditional plan. We then compute the expected profit of each provider and take the ratio.

We previously showed that if $\kappa_p < (D - \tilde{D})/\tilde{D}$ then the personalized plan is cheaper. Using the fact that $x = \tilde{D}/D$ this means that if $x < 1/(1+\kappa_p)$ then the personalized plan is cheaper. Using the price in 6 and the fact that $\tilde{T} = T$, the profit of the personalized plan is $F_p = \kappa_p \alpha \tilde{D} = \kappa_p \alpha x D$. Therefore the expected profit of the personalized provider is given by

$$E_p = \int_0^{\frac{1}{1+\kappa_p}} \kappa_p \alpha D f(x) x dx \quad (8)$$

The profit of the traditional plan (with $\kappa_t = 0$) is $F_t = \alpha(D - \tilde{D}) = \alpha D(1-x)$. Therefore the expected profit of the traditional provider is given by

$$E_t = \int_{\frac{1}{1+\kappa_p}}^1 \alpha D f(x)(1-x) dx \quad (9)$$

We can therefore write the ratio of these costs as

$$G = \kappa_p \frac{\int_0^{\frac{1}{1+\kappa_p}} f(x) x dx}{\int_{\frac{1}{1+\kappa_p}}^1 f(x)(1-x) dx} \quad (10)$$

Let us consider the PDF given by

$$f(x) = (n+1)x^n \qquad n = 2, 3, \dots \quad (11)$$

As n increases, more customers use a larger fraction of their data. In Figure 3 we plot this PDF for various values of n.

Using this PDF we can compute

$$\int_0^{\frac{1}{1+\kappa_p}} f(x) x dx = \frac{n+1}{(n+2)(1+\kappa_p)^{n+2}} \quad (12)$$

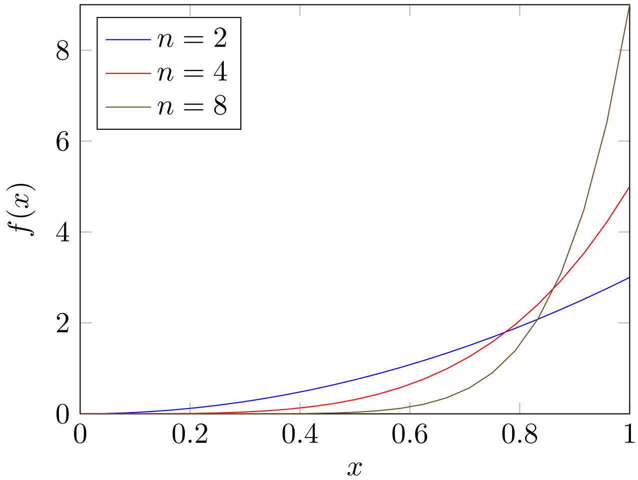

Fig. 3. Probability Distribution Function as n is varied

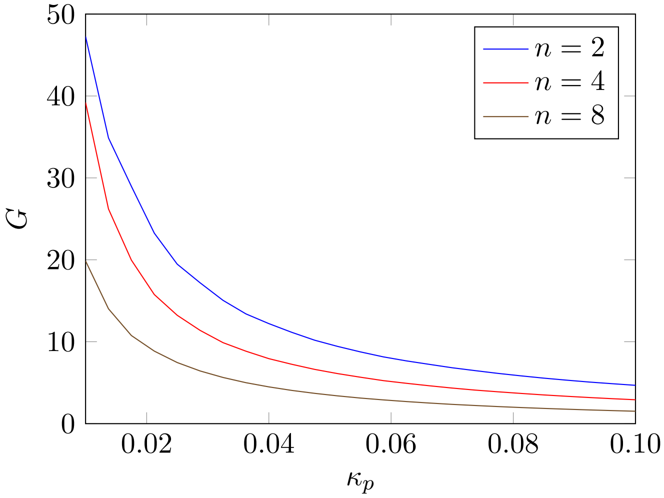

Fig. 4. Ratio of Profits as a Function of κ_p for $n = 2, 4, 8$

and

$$\int_{\frac{1}{1+\kappa_p}}^{1} f(x)(1-x)dx = \frac{1}{n+2}\left(1 + \frac{n+1}{(1+\kappa_p)^{n+2}}\right) - \frac{1}{(1+\kappa_p)^{n+1}}. \quad (13)$$

We can now use 12 and 13 to obtain the profit ratio G. This ratio is plotted in Figure 4. We find that even for relatively large values of κ_p, the expected profit for the personalized plan provider is greater than that of the traditional plan provider. We can repeat this analysis for the case of those users that run out of data before expiration of their plan (i.e. $\tilde{T} < T$) and obtain similar results.

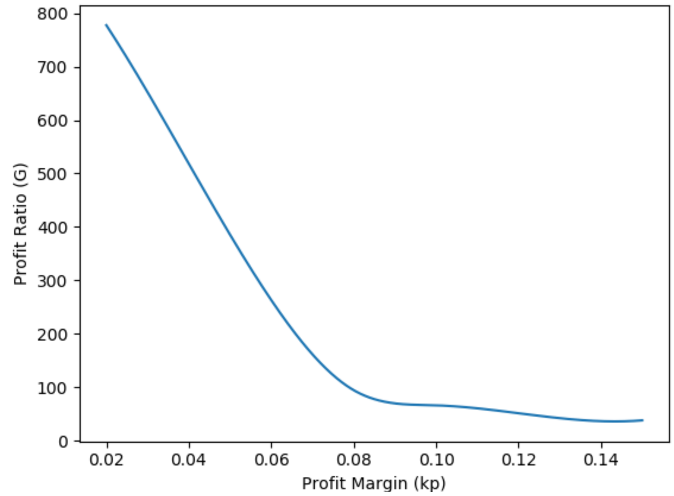

Fig. 5. Ratio of Profits as a Function of κ_p for Expired Plans

VII. Numerical Results

Numerical results were obtained to determine the effectiveness of this approach with real data. The dataset comprised of 750,000 records and was provided by a real provider with 22 different prepaid pricing plans.

We again compute traditional and personalized plan prices and assume that customers choose the provider with the lower price. We then determine the overall profit for the two providers and plot the ratios as in the previous section for κ_p values ranging from 0.02 to 0.15.

Although statistics showed that 98.74% of customers have their prepaid plans expire before the data is consumed, the case where users exhaust their plans, before expiry, is also examined. For these customers, the duration was investigated to calculate the fraction x. The profit ratio G is plotted in Figure 5 for expired plans and in Figure 6 for exhausted plans.

The results demonstrate the same relationship found within the illustrative example; as the profit margin for the personalized plan decreases, the per customer profit also decreases. However, more customers are attracted to the provider with personalized plans, due to a cheaper cost, and thus, less customers remain on the traditional plan, leading to a larger profit ratio.

Additionally, as the profit margin for the personalized plan is increased, the per customer profit goes up but more customers remain on the traditional plan since it becomes more competitive. The result is a reduction in overall revenue for the personalized plan provider when compared with the traditional plan provider.

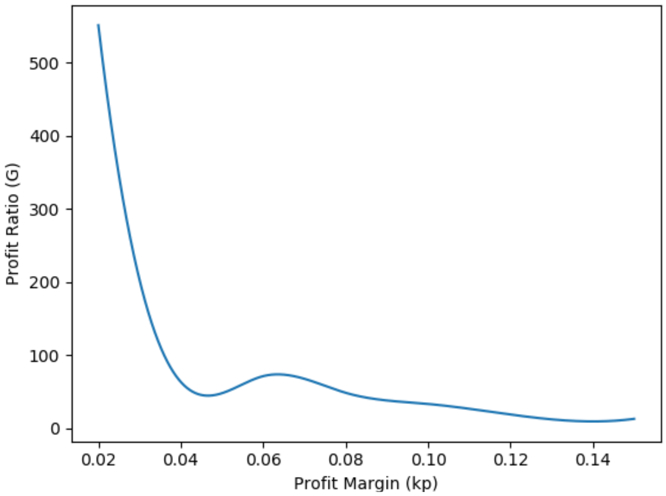

Fig. 6. Ratio of Profits as a Function of κ_p for Exhausted Plans

VIII. Conclusion and Future Work

We developed a personalized approach to mitigate customer churn and improve revenue in a prepaid and E-SIM context. We then formulated methods to determine optimal personalized pricing and plans for customers, and computed the profits and the profit ratio for traditional and personalized plans.

The effectiveness of the approach was demonstrated via numerical results, verifying that, as the profit margin decreased, the profit ratio increased, and the provider gained greater revenue through personalized plans. Given these results, mobile providers can now produce better prepaid plans and make more accurate decisions about their projected bundles and pricing.

Although our examples focused on the case of users running out of time before running out of data, the same results hold for the case where users exhaust data before time. In the future we plan to deploy this approach on a trial basis to determine its effectiveness in the real world.

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