Soft-Churn: Optimal Switching between Prepaid Data Subscriptions on E-SIM support Smartphones

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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, can choose the provider with the most cost effective data plan. This means that cellular providers must now take into account "soft-churn", where the consumer dynamically switches between multiple plans from multiple providers, in addition to the more traditional churn where a consumer switches providers. This means that data pricing for such consumers must now be more personalized in order to be competitive and maximize profits. We determine the optimal personalized prepaid plan for such users while providing a competitive advantage to the provider. Examples are provided to demonstrate the benefit and numerical results corroborate our premise that these personalized pricing plans can, in fact, increase provider revenue.**

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

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 involves customers who pay for service generally 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.

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

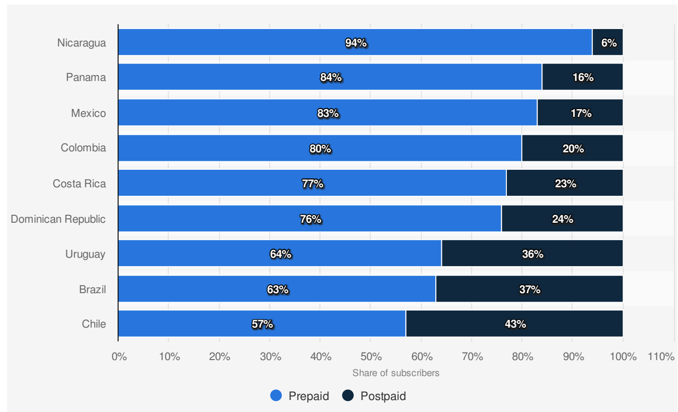

Fig. 1. Distribution of mobile subscribers in selected countries in Latin America in 2017, by contract type [1]

the caller. Currently, roughly 15 billion devices are equipped with physical SIM cards. However, these physical SIM cards occupy significant space on the device, can be stolen, is easily damaged, and requires unnecessary maintenance and management [2]. With recent advances in wireless and storage technologies, the embedded SIM (E-SIM), which consists of a tamper resistant module and software downloadable over-the-air, has become a popular alternative [3].

The E-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 [4]. Therefore, a customer may choose between plans, but they would need to have a E-SIM 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. This introduces flexibility of customer choice, allowing for the potential to increase soft churn [4], as well as fiercer competition amongst providers. 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. [5], the annual churn rate ranges from 20% to 40% for most global mobile telecommunications providers. Furthermore, prepaid customers present unique challenges since they can cease their activity without notice and are not contractually bound to their provider. The aim of this paper is to examine the potential behaviour of customers that switch from one provider to another through E-SIMs, where soft churn occurs.

The remainder of this paper is structured as follows, Section 2 describes the related work and contributions, Section 3 explains the traditional prepaid pricing model, personalized plans model and soft churn model with multiple providers, Section 4 jumps into an illustrative example which is followed by the numerical results in Section 5. We conclude in Section 6 and discuss directions for our future work.

II. Related Work and Contributions

Predicting customer churn is a supervised classification problem, meaning that customers can either churn (churners), or not churn (non-churners) [6]. There are several factors that can contribute to this 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 [7]. Similarly, Rajeswari and Ravilochanan found that churn was impacted by issues related to technology-based services, network coverage, network speed and complaint resolution [8], further validated via research in Turkey with other factors such as data usage, type of plan, and campaign awareness [9].

However, these factors vary for different industries [10] and prior research have suggested that the reliance on these customer attributes for traditional churn, may be insufficient when considering prepaid plans [6]. Prepaid customers are not bound to service providers and tend to be less loyal with a higher percentage of churn in comparison to postpaid customers [11] [12]. The same can be applied to soft churn with multiple providers. Comparative studies of prepaid and postpaid customers done to develop prepaid churn models, have found that the price of plans, usage pattern [13], [14], the quality of service [13], ease of use, and having multi-sims [14], are important factors when predicting prepaid churn. Customers tend to switch to the providers with the better prices, as well as services that are used by their family and friends [13]. Moreover, upon extension of a logistic model on the diffusion and dis-adoption rates, of 12 emerging markets and developing economies, it was discovered that lower prepaid prices increased the dissemination of prepaid mobile phones and lowered churn rates. Thus, providers who successfully develop affordable mobile technologies, can gain a competitive advantage by reducing prepaid prices for said technologies, and increasing the services [15]. This paper will examine the likelihood of churn for users with multiple sims, with an emphasis on the price of plans and data coverage.

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 where customers' usage behaviour is not considered [16]. Additionally, customer satisfaction is lowered due to their limited range of plan options, and, if a customer does not exhaust their plan, the remaining data would be forfeited. [17].

Dynamic plans determine optimal selling prices that can be easily and frequently adjusted [18]. There are currently no studies that have investigated the dynamic approach pertaining to E-SIMs, and only a few that analysed prepaid mobile users. To eliminate issues relating to static plans mentioned above, Lim, Alrshdan and Al-Maatouk [17] proposed a prepaid pricing scheme that provides customized plans to mobile consumers, allowing them to enter the amount of data and duration they wish to use. Another recent approach to grant providers a competitive edge, involves using multiple attributes of prepaid plans to develop dynamic pricing schemes that are personalized to the consumers' preferences, also known as the Product Line Design (PLD) approach. Deterministic scenario-based mathematical models were developed to assist in the design of these prepaid plans based on the assumption that, a network is built in advance, and there are no additional fixed cost to factor into the decision making. Using sensitivity analysis to examine how changes within various prepaid factors affect the revenue for mobile providers, they found that the consumers' purchase frequency, and their preferences for certain prepaid factors, had the most impact [19].

Several studies [20]–[22] have also shown that dynamic time-dependent pricing can be used for revenue optimization regarding Internet Service Providers (ISPs). Using this approach, Joe-Wong et al. found that ISP profit increased as users consumed more data during specific times [21]. Additionally, a modified sequential dynamic pricing for mobile networks that considers network congestion, as well as a dynamic pricing scheme, was studied [22]. As hypothesized [17], in comparison to providers that used the baseline static pricing scheme, the dynamic pricing schemes benefited the providers via increasing the provider's revenue, and the customers via maximizing their utilities. Others [23] [24] examined personalized mobile strategies, and it was found that, this engagement-based targeting, generated 101.84% more revenue compared to non-personalized targeting.

The approach proposed in these papers assumes a customized and dynamic prepaid pricing scheme that caters to the customer's needs. Our paper expands on the dynamic approach where we will examine personalized pricing plans, and develop a model to investigate the switching behaviour of customers when approached with these customized plans. 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 [4]. Additional business aspects of E-Sims are discussed in [25].

Note that, in this study, we do not take into account certain factors that may affect a customer's choice in provider. These factors can include the quality of service provided (e.g., see [26] for an analysis of pricing based on Quality of Service) and other business constraints, rules and offers. We plan to investigate these factors in a later study.

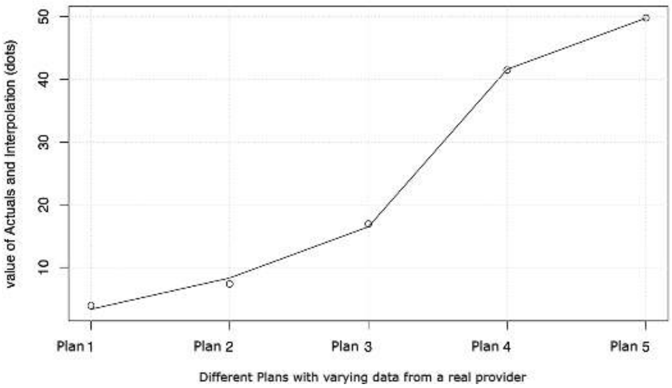

Fig. 2. Price (solid line) and Regression Estimates (circles) for 5 Plans

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 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 a real cellular provider. This provider has 5 different plans with varying data, time allowances and prices for each plan. Using the above model, we used linear regression to determine estimates of the function parameters α, β and γ and obtained the following pricing equation.

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

This implies a fixed cost (including profit) 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. The x axis represents each of the five plans.

We repeated this process for a competitor of this cellular 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 the following relationship,

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

Therefore, the fixed cost is \$2.32 while the per resource (GB or day) cost is \$1.87, compared to \$1.73 (\$0.83 + \$0.90) 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 extract the benefits 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 which we can compute from historical data. Furthermore, suppose that the customer knows how long they wish to use the plan, $\hat{T}$ (e.g., 30 days). 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 is given by

$$P = (1+\kappa)(\alpha R\hat{T} + \beta\hat{T} + \gamma) \tag{4}$$

Note that such personalized plans are always optimal for the customer at the expense of the provider as these plans are customized based on users preferences, where other factors such as the speed and quality of the plan stays the same. 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 where the optimal plan would allow for maximum utility usage, 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 [17] [23] [24].

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 consider a scenario with two providers. We can extend to the case of more than two providers by providing the same analysis to each pair of providers and choosing the best. 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), network speed and quality, are the same for both but that the profit margins are κ_t (profit margin for traditional plans) and κ_p (profit margin for personalized plans) 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

$$F_t = (1+\kappa_t)(\alpha D + \beta T + \gamma) - (\alpha \tilde{D} + \beta T + \gamma) \quad (5)$$

while for the personalized plan, the profit is

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

One can argue that the traditional provider can lower their profit margin in order to be competitive with the personalized plan provider, avoiding loss of 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 $\tilde{D} \leq D$ denote the data used by the customer, and let $\tilde{T} \leq T$ 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.

$$P_p = (1+\kappa_p)(\alpha \tilde{D} + \beta \tilde{T}) + \gamma \quad (7)$$

Note that the minimum price for the traditional approach is

$$P_t(\kappa_t = 0) = \alpha D + \beta T + \gamma \quad (8)$$

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 demonstrate 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. Based on historical purchase data via a real provider, it was discovered that the majority of customers purchase the cheapest plans with most data coverage where other factors such as network speed and quality stay the same. Thus, assuming that the speed and quality is similar for both providers, 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. Note that we will take into account the impact of different speed and quality in a later study. 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 7 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

$$E_p = \int_0^{\frac{1}{1+\kappa_p}} \kappa_p \alpha D f(x) x dx \quad (9)$$

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

$$E_t = \int_{\frac{1}{1+\kappa_p}}^1 \alpha D f(x)(1-x) dx \quad (10)$$

We can therefore write the ratio of these costs as

$$G = \kappa_p \frac{\int_0^{\frac{1}{1+\kappa_p}} f(x) x dx}{\int_{\frac{1}{1+\kappa_p}}^1 f(x)(1-x) dx} \quad (11)$$

Let us consider the following Probability Distribution Function (PDF) given by

$$f(x) = (n+1)x^n \qquad n = 2, 3, \ldots \quad (12)$$

Here the parameter n can be used to vary the behaviour of a customer. As n increases, users exhaust their data closer to expiration date of the plan. For a given n, the expected fraction of data they use before expiration of their plan is given by $\frac{n+1}{n+2}$, and so, customers make fuller use of their plan the higher the value of n. In Figure 3 we plot this PDF for various values of n. Using this PDF we can compute

$$\int_0^{\frac{1}{1+\kappa_p}} f(x) x dx = \frac{n+1}{(n+2)(1+\kappa_p)^{n+2}} \quad (13)$$

and

$$\int_{\frac{1}{1+\kappa_p}}^1 f(x)(1-x) dx = \frac{1}{n+2}\left(1 + \frac{n+1}{(1+\kappa_p)^{n+2}}\right) - \frac{1}{(1+\kappa_p)^{n+1}}. \quad (14)$$

We can now use 13 and 14 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

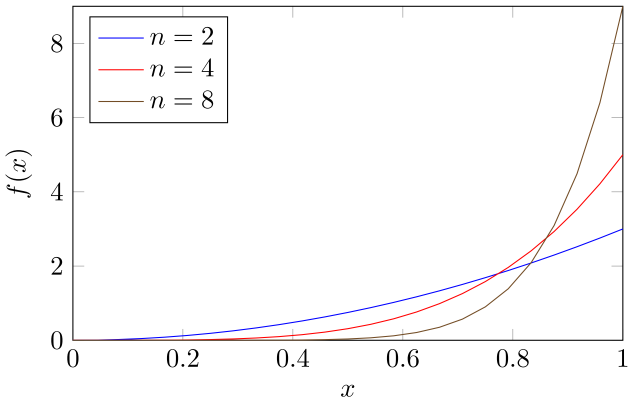

Fig. 3. Probability Distribution Function as n is varied

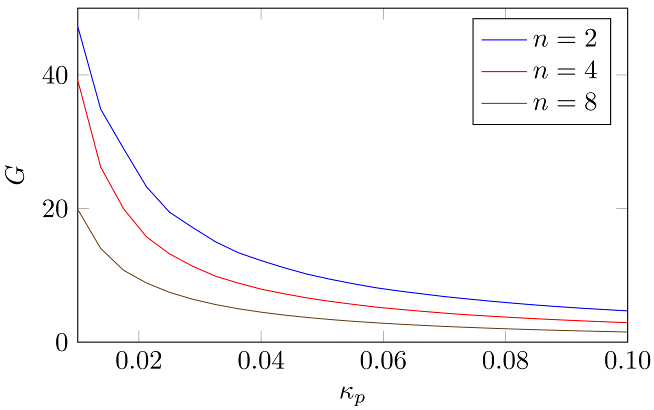

Fig. 4. Ratio of Profits as a Function of κ_p for $n = 2, 4, 8$

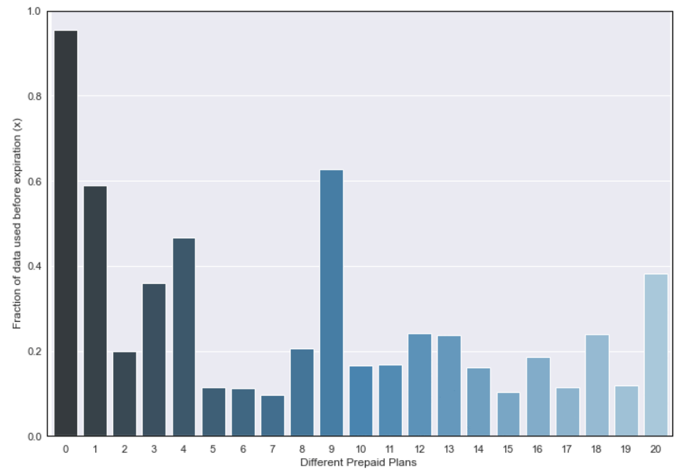

Fig. 5. Average fraction of data usage used before expiration for 20 actual plans

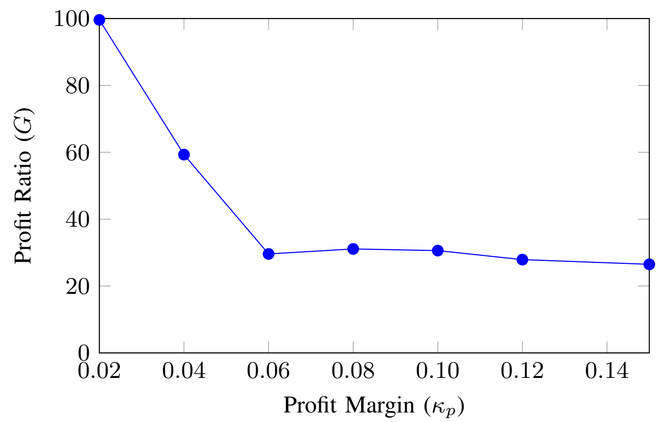

Fig. 6. Ratio of Profits as a Function of κ_p for Expired Plans

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. To get an idea of customers usage behavior before expiration for actual users, we evaluated the expected fraction of data used before expiration, x, for different subscription plans via a real provider. This is provided in Figure 5.

Here we find that users of plan 0 consume 95% of their data before their plan expires. On the other hand, this usage is only about 7% for plan 7, showing that data usage can vary drastically. Aforementioned, customers with a smaller fraction x of data usage can benefit more from a personalized plan. Given that x fell below 50% for the majority of plans, these customers can obtain optimal data plans that results in full data usage at the end of their plan, and this provider can expand their revenue significantly through these personalized plans.

VII. Numerical Results

Numerical results were obtained to determine the effectiveness of this approach with real data. Six months of data was supplied by an actual cellular provider with 22 different prepaid pricing plans and 589,242 users. Since this data was obtained via a telecommunications provider, it is confidential and has been made anonymous. Source code and anonymized data is available on our GitHub repository [27]. 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 approaches, and determine the ratios as in the previous section, for κ_p values ranging from 0.02 to 0.15. The profit ratio G is plotted in Figure 6 for the case of expired plans.

Although we find 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. In this case, x is the ratio of the time before data is exhausted to the total plan length and G is plotted in Figure 7.

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, since these plans suit customers data needs, allowing customers to achieve higher utilities for a cheaper cost, there is an increase in customer satisfaction. Thus more customers are attracted to the provider with personalized plans, and less customers remain on the traditional plan, leading to a larger profit ratio for the provider. Analysis on expired plans revealed

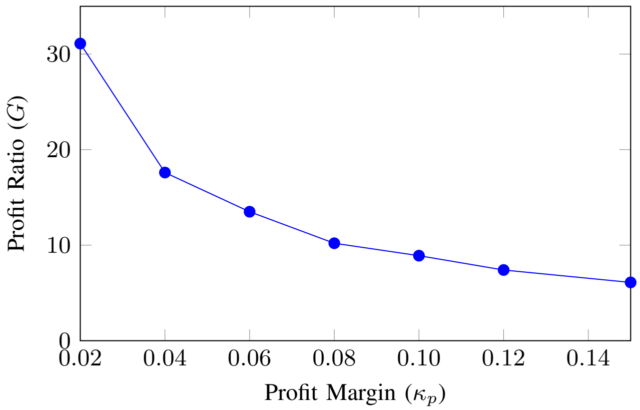

Fig. 7. Ratio of Profits as a Function of κ_p for Exhausted Plans

that the profit ratio was larger than exhausted plans, with values ranging from 26 to 100, proving that these customers tend to benefit more. The profit ratio for exhausted plans were still high, ranging from 6 to 31, showing the effectiveness that personalized plans can have on profit.

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 plans for customers and evaluated the behaviour of customers when presented with the option of these plans. Using these methods, the profits and profit ratio for traditional and personalized plans were demonstrated through an illustrative example, as well as with real data.

Although we focused on two providers, the results will also hold for more than two providers. In that case, the personalized approach can be compared with each of the traditional approaches, and in each case it will provide better profit margins. As we focused on price, we could not take into account the multitude of business rules that individual companies may have and plan to address this, as well as the issue of network speed and quality, in the future. We also intend to deploy a mobile application that would provide recommendations and automatically choose the provider that is best for the user on a periodic basis.

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