Maximizing Revenue in the Mobile Social Data Market via Dynamic Pricing Considering Network Effects

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Abstract- The ever-increasing demand for mobile bandwidth in wireless social networks has made the need for a fair pricing mechanism for socially enabled services paramount. It seems to reason that, notwithstanding the prevalence of static pricing in the real data market, more revenue would be generated by dynamically changing prices. Maximising the expected long-term revenue via the development of the optimal dynamic pricing strategy should be your top priority. This study takes a look at the social data industry by analysing it via the sequential dynamic pricing structure of a monopoly mobile network operator. Over the course of many time periods, the operator (the seller) offers each mobile user (the buyer) a fixed price in the market. This process repeats itself. The proposed strategy boosts the need for social data by capitalising on the network effects generated by mobile users' activities. Wireless network congestion, caused by limited radio resources, is also included into the pricing process. Then, to guarantee that mobile clients are treated equitably according to their unique utilities, we propose an amended sequential pricing structure. To have a better understanding, we go further into a concurrent dynamic pricing system in which the operator pays for the data all at once. We show that the proposed dynamic pricing system outperforms the baseline static pricing scheme in terms of operator revenue and consumer total utilities. Our social network is constructed using real datasets and the Erd˘os-R'enyi (ER) model in order to evaluate performance. According to the numbers, operators may potentially make a lot more money by switching to dynamic pricing systems from static ones.

Keywords-- Network economics, mobile social data market, network effects, congestion effects, dynamic pricing, revenue maximization.

I. INTRODUCTION

The explosion of social app services on mobile platforms has led to a surge in the demand for social media data collected from mobile devices. The ability to interact with others online via mobile social services is a major draw for consumers, who are increasingly spending time on these sites [1]. Nearly three billion individuals, or 57% of the total mobile internet users, used their mobile devices to visit social media sites in 2018 [2]. Users' increased usage of social services leads to stronger social relationships, which boosts their consumption of social data and interactions with others, creating a positive feedback loop [3]. According to [2], the proportion of cellular data use attributable to social media activity on mobile platforms has been rising over the last several years and now exceeds 50%. It stands to reason that friends of an active user would likely increase their own involvement levels in a social service. "Network effect" is the economic term for this occurrence [4]. It happens when other users' demands have a positive effect on one user's need for social data. For obvious financial reasons, mobile network providers would love to have their users—and, by implication, their potential customers—use more social data. After all, it is the users who pay for the data consumed by social services. When there are strong network effects, the mobile network operator usually ends up with more money [5, 6]."Network effect" has been the subject of several articles in economics and sociology [7]. Several studies have proposed pricing under equilibrium conditions as a means of controlling the operation of social networks with respect to network effects [8, 9]. Research on network effects has also broadened to include communication networks such as the Internet, mobile ad hoc networks, and peer-to-peer networks, in addition to more classic areas of network economics [3, 11, 12]. This potential benefit, however, remains a pipe dream due to the limitations of physical communication networks, such as bandwidth. This is because customers are less likely to access and use more data if doing so causes congestion, such service delay, which discourages them from expanding their data demand. Increased congestion is a major problem for the network operator since it reduces their revenue [5, 13]. Therefore, the network effects in the social domain and the congestion effects in the network domain both influence mobile users' data consumption. On the other hand, this issue has received little attention from network operators in the literature. Network operators have the opportunity to boost their revenue by strategically pricing services to influence client demand [14]. At first, the operator's only strategy for attracting users was static pricing, which took the shape of simple flat-rate data contracts. As more and more people watch films and use apps online, dynamic pricing has emerged as a practical way to handle customers' erratic data needs. The basic premise is that smart use of pricing to affect demand may assist solve underutilised capacity and increase revenue [15]. To maintain a steady supply and demand, mobile message pricing are dynamically changed on a daily or even hourly basis by businesses such as MTN in Uganda and Uninor in India [14], [16]. In addition, China Telecom provides its clients with cheaper data at less busy times, such as the night; otherwise, the charge does not change.Dynamic pricing has lately been a hot subject in the revenue management literature, and it has numerous practical applications in areas such as cloud computing[15], smart data[16], smart grid[17], and power control [18]. The capacity to change rates gives mobile network operators the chance to optimise their profits in the long run by pursuing the optimal dynamic pricing strategy. Having established the stochastic buyer (user) demand model, most dynamic pricing publications (e.g., [15]-[18]) mainly target the seller's point of view. In other words, they prioritise the seller's profit maximisation above client connections. Congestion effects and network effects are interdependent, which complicates interactions and has an even greater influence on customers' demand patterns. Academics have paid little attention to a major issue with dynamic pricing operations: the mobile data market's heavy reliance on network and congestion impacts. For the first time, this study looks at how mobile network operators, or vendors in the social data market, could optimally implement dynamic pricing schemes when selling social data to a group of mobile users in a setting where congestion and network effects affect the users' behaviour. The operator consistently and sequentially offers a set price to each customer over several time periods in our proposed sequential dynamic pricing mechanism. Given the frequency of data plan updates (e.g., once a month), it's crucial to consider the evolution of the operator-consumer dynamic. A brief synopsis of the main arguments presented in this paper follows:

The need for social data from mobile users is further augmented by our modelling of network effects in the social domain, which makes use of the structural aspects of social networks. In order to accurately reflect the limited availability of radio resources in a wireless network setting, the model also accounts for congestion effects in the domain of networks. In addition, we provide analytical proof that sequential dynamic pricing, as we have suggested, may lead to higher total utilities for mobile users and more income for mobile network operators compared to the current best static pricing scheme.

To gain more insights, the simultaneous dynamic pricing is developed in which the operator determines the pricing strategy at the beginning of each time period and users decide on their individual data demand in each time period simultaneously. We find the insights that the operator tends to offer the discount price to the users with more social influence which may bring more potential users subsequently, and the discount price is still slightly higher for the users with more influence since the new coming users may lead to the decrease of user utility because of congestion effects.

We examine two social graphs in order to define the nature of the network effects resulting from social networks. The Erd˘os-R'enyi (ER) model is used to generate the first graph [19], while the Brightkite dataset is used to build the second graph [20]. The results of the performance review back up the claim that operators may significantly increase their income by using dynamic pricing systems instead of static ones.

II. RELATED WORKS

The data pricing plan for the network operators is a body of literature that is relevant to our work. Its purpose is to provide lucrative business opportunities while also facilitating the creation of user-friendly services [14], [21]. There are a number of new and interesting data pricing schemes that network operators have been dealing with recently, such as sponsored data plans[23], [24], and secondary data market schemes [22]. Nevertheless, when it comes to structuring data pricing, the majority of previous efforts fail to include the homophily phenomena, often known as network effects. A new paradigm for optimising and designing networks is the social component of mobile networking [5]. The data gained via social tie relationships will impact decision making, according to the authors of [25]. Using actual data analytics, the authors of [26] demonstrated the existence of network effects in communication services and used a straightforward measure to quantify these impacts. Network effects and service pricing have been studied together from an economic standpoint, drawing on [26] as an inspiration [9]. In the seminal paper [8], for instance, the authors looked at the service provider's pricing strategies with network effects taken into account. The authors addressed the topic of dynamic pricing strategies for divisible social products with network effects in references [27], [28]. Having said that, the user behaviours in the social domain were the only ones examined in the aforementioned research. Wireless networks and other physical networks often force users to share scarce communication resources like bandwidth. Hence, the physical domain congestion impact on user behaviours is also widespread [29]-[32]. For instance, when an Internet service provider has high subscriber demand, it might lead to congestion as a result of insufficient bandwidth and radio resources [33]. As a result, the model presented in references [8, 9, 27, 28] has a significant flaw: it isn't suitable for use in wireless network settings, where radio resources are limited and congestion is common. Therefore, it is unclear whether network operators continue to reap the benefits of network effects in the face of congestion.To make the most of social data services, it's better to create prices that take congestion and network impacts into account holistically. This way, network operators can maximise their income. As far as we are aware, no other study has suggested data pricing systems that take both congestion and network impacts into account simultaneously. The only one that comes close is [5]. Expanding on the model given in [8], the authors in [5] modelled the interaction between a network operator and mobile users as a two-stage Stackelberg game. The leading service provider sets the fee for users in Stage I, the highest level of the game. Next, at Stage II's lower pricing point, users who are following each other make a simultaneous decision on the data demand that maximises their individual utilities. However, the authors of [5] only used a one-shot game to simulate the relationship between mobile consumers and the network provider using static pricing. This means the operator is unable to make use of its strategy-modification capabilities in light of past data. We investigate the sequential dynamic pricing method in [35], which accounts for this void by considering user behaviour in the context of network and congestion impacts. Additional findings from analyses are also included in this publication. In particular, the social justice problem is addressed by using the sequential dynamic pricing method. In addition, we look at the concurrent dynamic pricing to learn more. The table below summarises the main points that set this study apart from most similar ones. I.

Table I Comparison Of Our Work With Most Related Works On Pricing

Ref.	Pricing goods	Pricing scheme	Network effects	Congestion effects
[29], [30], [32]	Networking resources	Static pricing	×	✓
[31]	Networking resources	Dynamic pricing	×	✓
[16], [33]	Mobile data	Dynamic pricing	×	×
[8], [9], [34]	Social goods	Static pricing	✓	×
[27], [28]	Social goods	Dynamic pricing	✓	×
[5]	Mobile social data	Static pricing	✓	✓
Ours	Mobile social data	Dynamic pricing	✓	✓

III. PROPOSED METHOD

A. Basic static model

Here, Ꝁ ={1,2,3………N} denotes a set of mobile users in a social data market. Every customer, denoted as i in the set Ꝁ, chooses a non-negative data demand from a Mobile Network Operator (MNO), where xi is a number between zero and infinity, in order to access social services. Let x = (x1,..., xN) denote the demand profile for all users, and let x-i denote the demand profile for user i minus that profile. In a nutshell, the user with a lack of long-term vision will choose the option that maximises the price per data unit pi. Here is how the user's utility is defined in a more formal sense:Improving one's social network standing may be as simple as joining in on the activities of other members [3]. In particular, gij stands for the presumed one-way effect of user j on user i. When we say that users i and j have a reciprocal social tie, we say that gij = gji. For social connections that go both ways, however, the idea remains the same. With gii= 0, it is impossible for an individual user to influence oneself in any manner. The amount that the MNO deducts from user i under usage-based pricing is pixi. Here we have a look at the discriminatory pricing scheme, where the MNO charges different consumers different amounts [36], [37]. More importantly, consumers may experience congestion, such as service delays, due to mobile networks' limited radio resources, when the demand for social data grows all at once. Therefore, we investigate user behaviour by integrating the effects of network size and congestion. The demand of all users influences each user's congestion experience, as indicated by the quadratic sum form. The marginal cost of congestion also increases as total demand climbs. Theoretically, the vendor (MNO) may charge different customers different amounts (discriminatory pricing) if they knew everything about the social network [38]. Here is the declared purpose of the MNO: maximisation of revenue:

The two-stage Stackelberg game is a suitable tool for simulating the MNO-user dialogue [5, 13, 39]. The leader (MNO) chooses price pi at the beginning of Stage I to maximise its profits. Users (i.e., followers) in Stage II's bottom half maximise utility by determining their own data demand xi, taking into consideration the price pi set by the MNO. At first, we utilise backward induction methods to study a set of strategies where the Nash equilibrium (i.e., no user deviates based on the offered price) is reached. This Nash equilibrium could lead us to delve more into the optimal MNO pricing.

B. Dynamic model extension

Here, Ꝁ ={1,2,3………N} denotes a set of mobile users in a social data market. Every customer, denoted as i in the set Ꝁ, chooses a non-negative data demand from a Mobile Network Operator (MNO), where xi is a number between zero and infinity, in order to access social services. Let x = (x1,..., xN) denote the demand profile for all users, and let x-i denote the demand profile for user i minus that profile. In a nutshell, the user with a lack of long-term vision will choose the option that maximises the price per data unit pi. Here is how the user's utility is defined in a more formal sense:Improving one's social network standing may be as simple as joining in on the activities of other members [3]. In particular, gij stands for the presumed one-way effect of user j on user i. When we say that users i and j have a reciprocal social tie, we say that gij = gji. For social connections that go both ways, however, the idea remains the same. With gii= 0, it is impossible for an individual user to influence oneself in any manner. The amount that the MNO deducts from user i under usage-based pricing is pixi. Here we have a look at the discriminatory pricing scheme, where the MNO charges different consumers different amounts [36], [37]. More importantly, consumers may experience congestion, such as service delays, due to mobile networks' limited radio resources, when the demand for social data grows all at once. Therefore, we investigate user behaviour by integrating the effects of network size and congestion. The demand of all users influences each user's congestion experience, as indicated by the quadratic sum form. The marginal cost of congestion also increases as total demand climbs. Theoretically, the vendor (MNO) may charge different customers different amounts (discriminatory pricing) if they knew everything about the social network [38]. Here is the declared purpose of the MNO: maximisation of revenue:

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Algorithm 1 : Sequential dynamic pricing scheme for mobile social data market

Require: $\widetilde{x}^{(k)} = [\widetilde{x}_1^{(k)}, \widetilde{x}_2^{(k)}, \dots \widetilde{x}_N^{(k)}]^\top$.

for each time period k **do**

  1): Obtain social data demand in the time period k: $\widetilde{\mathbf{x}}^{(k)} = [2\mathbf{\Lambda}_c - \mathbf{G} + \mathcal{C}]^{-1}\mathbf{T}^{k-1}\mathbf{a}$, where $\mathbf{T} = \mathbf{I} - (\mathbf{\Lambda} - \mathbf{G} + \mathcal{C})(2\mathbf{\Lambda}_c - \mathbf{G} + \mathcal{C})^{-1}$.

  2): Obtain total social data demand until time period k: $\widetilde{y}_i^{(k)} = \sum_{k'=1}^{k-1} \widetilde{x}_i^{(k')}$.

  3): Set the order of users as $\mathcal{R} = 1, 2, \dots, N$.

  4): Obtain the prices charged to users for time period k: $\widetilde{p}_i^{(k)} = a_i - 2b_i\left(\widetilde{y}_i^{(k-1)} + \widetilde{x}_i^{(k)}\right) + \sum_{j\in\mathcal{N}} g_{ij}\widetilde{y}_j^{(k-1)} + \sum_{j<i} g_{ji}\widetilde{x}_j^{(k)} - c\widetilde{y}_i^{(k-1)} - c\sum_{j<i}\widetilde{x}_j^{(k)}$.

  Output: $[\widetilde{p}_1^{(k)}, \widetilde{p}_2^{(k)}, \dots, \widetilde{p}_N^{(k)}]^\top$

end for

IV. RESULTS AND DISCUSSION

We conduct the simulations in this part to demonstrate the impact of different variables on the proposed dynamic pricing systems. By modelling the social network G using the Erdˇos-R'enyi (ER) graph, the social characteristics may be represented. Any two nodes in the ER network might be friends with each other with the same probability, Pe. We also simulate the real social network using the actual data trail from Brightkite [20]. Brightkite is a social networking program for mobile phones that allows users to have direct, unfiltered conversations with one another. We create the social network by picking N users at random from the real dataset, where N = 10, 15,..., 50. For each set of N users, we calculate the mean results after 500 repetitions. Figure 1 shows the correlation between the volume of social connections, the probability of social ties, and the number of users in the real dataset. Sequential Dynamic Pricing (SeqDP) may guarantee convergence of MNO revenue and user total utilities throughout the first 40 time periods, as shown in Figures 2 and 3. Next, we compare the two users' individual utility under SeqDP with and without social fairness consideration; Figure 4 shows the results. This demonstrates that the updated SeqDP has a chance of achieving social fairness with respect to the network utility of the person. We may evaluate the total utility of mobile users in relation to social data demand and the MNO's revenue by comparing the proposed SeqDP's income and total utilities with those of OSP (Figures 5 and 6). As a control situation, our performance assessments also include the scenario when user needs for social data are unrelated. Our proposed socially aware user benefit is meaningless if a user has no social connections at all. Additionally, we compare the ER-based social graph model's (social graph-ER) performance on the real dataset to that of the Brightkite-based social graph model (social graph-Brightkite).Total utilities increase when the chance of social edge increases, as seen in Figure 5. The proposed SeqDP outperforms OSP in terms of total utility as the probability of social edge increases. A person's total utility rises when the probability of social edge rises because they have more social neighbours and more additional benefits from their neighbours' social data need. Therefore, the SeqDP's MNO revenue rises as the risk of social edge does. As the probability of social edge increases, the fundamental concept is that the MNO's bottom line will profit from the increasing demand for social data caused by greater underlying network effects. The findings of the ER-based social graph model, which disregards social relationships entirely, corroborate this.

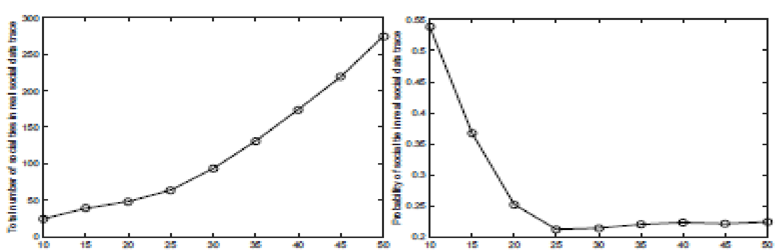

Figure 1. Real social data trace from Brightkite [20]: total number of social ties versus the number of users (left), and probability of social tie versus the number of users (right).

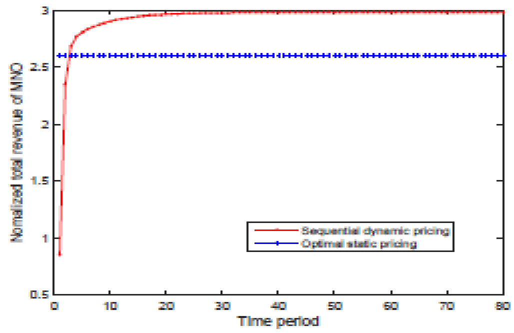

Figure 2. Normalized total revenue of the MNO versus time periods.

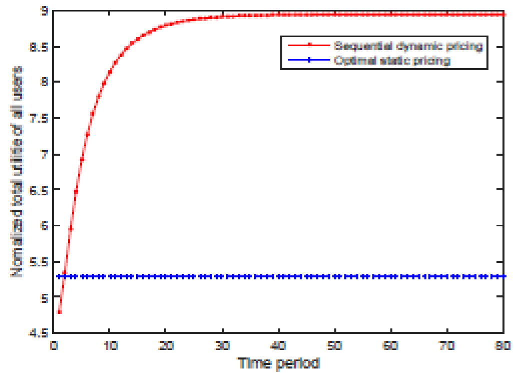

Figure 3. Normalized total utilities of mobile users versus time periods.

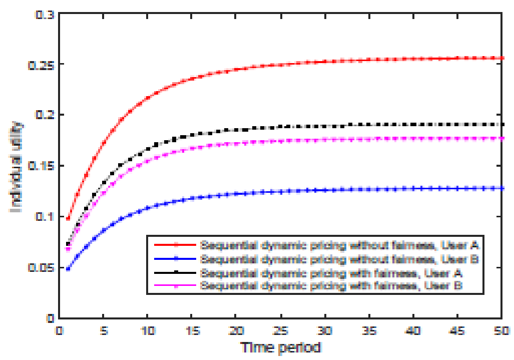

Figure 4. The illustration of individual utility of users with and without social fairness consideration.

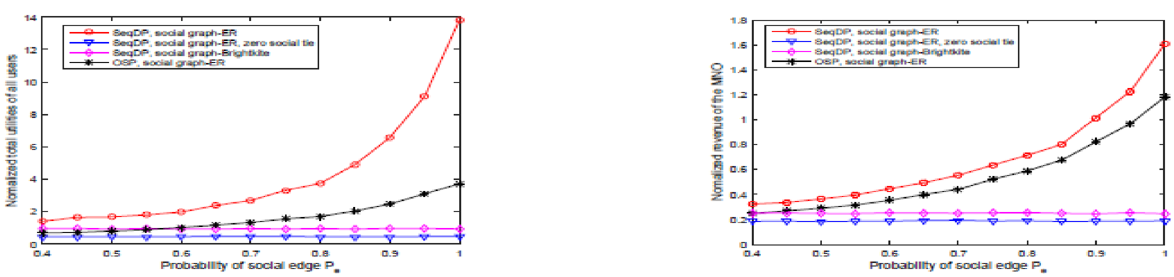

Figure 5. Normalized total utilities of users and normalized revenue of the MNO versus the probability of social edge.

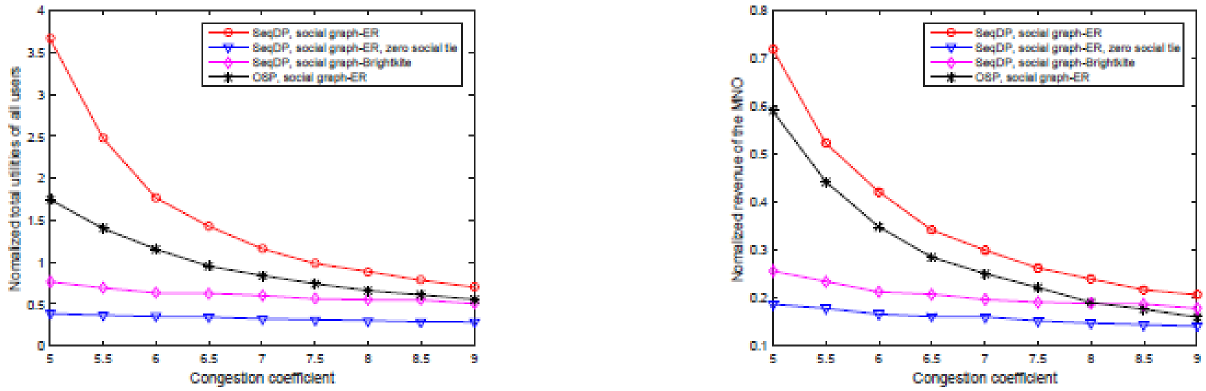

Figure 6. Normalized total utilities of users and normalized revenue of the MNO versus the congestion coefficient.

V. FUTURE SCOPE AND CONCLUSION

In this post, we have presented a method for optimising income in the mobile social data market via the use of dynamic pricing techniques. The network operator would systematically charge each user a set fee for accessing their social data across different time periods under our proposed sequential dynamic pricing scheme. Using the proposed pricing system, researchers have examined the implications of network effects in the social domain as well as the affects of congestion in the network domain. To confirm that the pricing schemes' dynamics are superior, we have conducted comprehensive performance evaluations utilising the Erd˘os-R’enyi graph and the social graph, both of which are based on real datasets. Using machine learning to determine the optimal parameter values in the real data market will allow us to make more informed and precise forecasts on user demand in our future studies. Congestion coefficients and network effects, for example, may have a temporal profile at different time points. Consequently, we will look at techniques to forecast the values of such parameters in a dynamic mobile social data market. Another interesting direction to go is to find out how sensitive theoretical results are. To be more precise, we'll include factors like congestion and network affects into the user utility calculation.

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