SCHEME OF SEQUENTIAL DYNAMIC PRICING FOR THE MOBILE SOCIAL DATA MARKET

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Abstract-

Mobile data usage is expanding dramatically in wireless social networks, and hence an effective pricing mechanism for social-enabled services is urgently required. Though static pricing is prominent in the real data market, price intuitively needs to be dynamically altered to create higher income. The main challenge is how to develop the ideal dynamic pricing system, with prospects for maximising the predicted long-term revenue. In this research, we explore the sequential dynamic pricing scheme of a monopoly mobile network operator in the social data market. In the market, the operator, i.e., the seller, individually offers each mobile user, i.e., the buyer, a given price in numerous time periods consecutively and again. The proposed scheme exploits the network effects in the mobile users' behaviours that boost the social data demand. Furthermore, owing to limited radio resource, the effect of wireless network congestion is taken into consideration in the pricing structure. Thereafter, we suggest a modified sequential pricing mechanism in order to promote social fairness among mobile users in terms of their individual utilities. To acquire further insights, we further examine a simultaneous dynamic pricing system in which the operator gives the data price concurrently. We analytically show that the suggested dynamic pricing scheme may assist the operator acquire better income and customers attain higher total utilities than those of the baseline static pricing scheme. We create the social graph using Erd˝os- R´enyi (ER) model and the actual dataset based social network for performance assessment. The numerical findings verify that the dynamism of pricing schemes over static ones may greatly boost the income of the operator.

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

I. INTRODUCTION

As mobile social apps like Facebook, Twitter, and WhatsApp exploded in popularity, so did the need for mobile social data. User interaction with each other is possible via mobile social services, which in turn leads to more time spent on social service websites [1]. There were over 3 billion social media users on mobile platforms in 2018, which accounts for 57% of all mobile users [2] in 2018. Reversely, the more social services consumers utilise and the more social links they have, the more social data they consume and the more interpersonal communication they have [3]. It has been shown in [2] that social media activity on mobile platforms account for more than half of total cellular data usage, and this ratio has been rising steadily in recent years. Increasing a user's participation in a social service is likely to enhance the activity of the user's social friends as well. Economic theory refers to this phenomena as the "network effect," which describes how the demand for social data from one user is influenced by the demand from other users [4]. As a result, the mobile network operator has an incentive to encourage more mobile users, i.e., prospective customers, to utilise the social services by consuming more social data. To put it another way: The more income a mobile service provider gets from its customers, the larger the network effects are. The term "network effect" is often used in both social and economic contexts [7]. According to a few current studies, the pricing under equilibrium circumstances and the functioning of a social network based on network effects may be figured out in a few ways. Even though it's considered one of the most important concerns in networking economics [10], the consequences of network effects have also been studied in communication networks such as the Internet [3], [11], [12]. Due to restricted bandwidth in physical communication networks such as Ethernet, this potential value is limited. As a result of increased congestion, e.g. service delay, consumers may be unable to access or consume as much data as they would want. Congestion is a substantial obstacle for the network operator, which results in decreased revenue [5],]. Consequently, not only are networks in the social realm prone to network effects, but so are networks themselves, due to the congestion effects. As a result, network operators have generally ignored this topic in the academic literature. Network operators may increase their income by using proper pricing techniques that directly impact the demand of their customers [14]. To entice customers, the operator at first simply offered basic flat-rate data contracts. Online applications and movies have made dynamic pricing a more viable option for adjusting to unanticipated user data use in recent years. For this reason, price should be used as a strategic tool for influencing demand and so generating more income [15]. According to MTN in Uganda and Uninor in India, mobile message prices might be dynamically altered after one day or even one hour in order to balance supply and demand [14, 16]. Also, China Telecom charges its customers a discount data rate during less congested hours, such as at night, and standard data fees when the network is more crowded, such as during the day. Cloud computing, smart data, smart grid, and power control are only a few examples of effective real-world uses of dynamic pricing in revenue management literature. The optimal dynamic pricing policy for a mobile network operator in order to maximise long-term revenue becomes attractive given the flexibility to change the price. Most publications on dynamic pricing, such as [15]–[18], solely concentrate on seller demand supplied by the stochastic buyer (user) demand model. In other words, they focus mostly on the seller's profit maximisation without taking into consideration the relationships between consumers. Because of this, interactions between users become more difficult because of the interdependencies that exist between them. As a result, dynamic pricing in the mobile data market faces a significant issue that has not yet been well addressed in the literature, given the prevalence of network effects and congestion effects. Our research is the first of its kind to examine how a mobile network operator, i.e., a seller in the social data market who sells social data to a group of mobile users, may optimise dynamic pricing schemes in the presence of network effects and congestion effects. Sequential dynamic pricing, in particular, is a method that allows operators to offer different prices to different customers over time. Time-varying interactions between operator and user are motivated by the fact that data plans typically have multiple versions that are released on a monthly or quarterly basis. As a result of this research, the following are the most important findings:

There is a rise in demand for mobile users' social data due to our model's incorporation of network structural elements. Congestion effects are also included into the network domain so that radio resources may be accurately captured in wireless network environments. Our suggested sequential dynamic pricing scheme, on the other hand, may allow the mobile network operator to acquire more income and mobile consumers to get higher total utility than those of the present optimum static pricing scheme.

As a result, the operator sets the pricing strategy at the beginning of each time period, and users decide on their individual data demand at the beginning of each time period at the same time. As a result, we find that the operator offers a discount price to those users who have more social influence, which may lead to an increase in future users, and that the discount price is slightly higher for those users who have more influence because the new users may reduce user utility due to congestion effects.

Consider two social graphs to describe the network impacts of social networks. There are two graphs, one based on the Erd os-R'enyi (ER) model, and the other based on the Brightkite dataset. According to the results of the assessment, dynamic pricing schemes may significantly increase the income of an operator over static pricing schemes.

II. RELATED WORKS

Network operators' data pricing schemes, which are intended to provide a lucrative business while also creating beneficial services for consumers, are an important part of our research [14], [21]. Rollover data plans, secondary data market schemes, and sponsored data plans [23], [24] are only some of the new and inventive data pricing schemes that network operators are dealing with. However, for the design of data pricing, most current research overlook the homophily phenomena, i.e. network effects. A new paradigm for network design and optimization is based on the social aspects of mobile networking [5]. Decisions are influenced by information gathered via social ties, according to the authors of [25]. [26] used actual data analysis to demonstrate the existence of network effects in communication services and used a simple measure to quantify such an impact. As a result of [26], network effects and service pricing have been taken into account together from an economic standpoint [9]. A pioneering study [8] examined service provider pricing structures in the face of network effects, for example. The dynamic pricing approach of divisible social commodities with network effects was described in [27] and [28]. However, the above studies only looked at user behaviour in the context of social interaction. Sharing bandwidth is a common occurrence in physical networks, such as wireless networks. As a result, the physical domain congestion impact on user behaviour is also widespread [29–32]. Due to limited bandwidth and radio resources, an Internet network operator's customers may experience congestion [33]. Consequently, it cannot be used in wireless network situations, where radio resource is limited and congestion might occur often, like the model presented in [8], [9], [27], [28]. Since the issue of whether network operators continue to profit from the network effects when congestion occurs remains unanswered. The ideal way for network operators to maximise their income from social data services is to create pricing that takes into account both network effects and congestion effects in a holistic manner. Only the study [5] has offered data pricing methods that take into account both network impacts and congestion effects, to our knowledge. The two-stage Stackelberg game model proposed in [8] was extended in [5] to describe the interaction between a network operator and mobile users. Service providers acting as leaders in the constructed game set the pricing for customers in the top Stage I. If the price in Stage II is lower, users who are operating as followers concurrently decide on the data demand in order to maximise their own individual utilities Yet [5] only used the one-shot game to simulate interactions between network operators and mobile consumers with unchanging pricing. As a result, the operator is unable to use its capacity to adjust its approach in reaction to the observed history. Accordingly, we investigate sequential dynamic pricing in [35], which incorporates both network impacts and congestion effects into price decisions. There are further analytical findings in this publication. When it comes to social justice, a sequential dynamic pricing strategy is used. As a further investigation, we take a look at simultaneous dynamic pricing. Table summarises the main distinctions between this study and most comparable papers. 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

In a social data market under our consideration, there is a set of mobile users $\mathcal{N} =\{1,2,3\ldots\ldots N\}$. Each mobile user $i \in \mathcal{N}$, i.e., the buyer, determines a non-negative quantity of the data demand from a Mobile Network Operator (MNO) for accessing social services, denoted by xi where xi ∈ $[0,\infty)$. Let x =(x1,……,xN) denote the demand profile of all the users and x_{-i} denote the demand profile without that of user i. Given the offered price per unit of data pi, the myopic user chooses the action that maximizes its utility. Formally, the utility of the user is formulated as follows:

$$u_i(x_i, \mathbf{x}_{-i}, p_i) = f_i(x_i) + \sum_{j\in\mathcal{N}} g_{ij}x_ix_j - \frac{c}{2}\left(\sum_{j\in\mathcal{N}} x_j\right)^2 - p_i(x_i). \quad (1)$$

In social networks, one user can enjoy an additional benefit from the actions of other users [3]. In particular, gij refers to the influence of user j on user i, which we assume to be unidirectional. In other words, gij = gji represents the social tie between users i and j, i.e., the social tie is reciprocal. Nevertheless, the same model can be applied to bidirectional social relations straightforwardly. Moreover, gii = 0 which means one user cannot influence oneself. The fee that the MNO charges to user i is equal to pixi, i.e., usage-based pricing. In this paper, we consider the case that the MNO can charge the different users with different prices, i.e., the discriminatory pricing scheme [36], [37]. More importantly, the users may experience congestion with an increase of social data demand at the same time, e.g., service delays, due to the limited radio resources in mobile networks. Therefore, we investigate the users' behaviors by jointly incorporating the network effects and congestion effects. The quadratic sum form reflects that the congestion experience of each user is affected by the demand of all the users. Also, the marginal cost of congestion increases as the total demand increases. We assume that the MNO, i.e., the seller, has complete information about the social network and can perfectly charge each user differently, i.e., discriminatory pricing1 [38]. The objective of the MNO is to maximize its revenue which is expressed as follows:

$$\Pi = \max_{p_i} \sum_{i\in\mathcal{N}} p_i x_i. \quad (2)$$

Naturally, the two-stage Stackelberg game can be adopted to model the interaction between the MNO and users [5], [13], [39]. In the upper Stage I, the MNO, i.e., the leader, determines price pi to maximize its revenue. In the lower Stage II, the users, i.e., the followers, decides on their individual data demand xi in order to maximize their utilities being aware of price pi set by the MNO. Using the backward induction methods, the existence and uniqueness of a set of strategies where no user deviates based on the given price, i.e., the Nash equilibrium, is investigated first. Based on this Nash equilibrium, the optimal pricing of the MNO can be further addressed.

B. Dynamic model extension

Multi-round dynamic pricing, as opposed to a one-round static pricing, is used in this case, when the MNO and users interact throughout numerous time periods, such as the day. An MNO's revenue and user utility maximisation may be examined simultaneously in such a framework, combining demand-side user interaction modelling, in order to examine several time periods simultaneously. As a matter of fact, we're thinking of selling the data sequentially. When considering sequential dynamic pricing, the MNO might give a regular or discounted price to further maximise revenue [34]. 2. For example, the MNO may provide discounts to encourage customers to acquire data early in the sequence.. Because of network effects, the data becomes more valuable to purchasers later in the series. Consequently, the MNO is able to collect more money from successive customers. In the following examples, you'll see that the sequential marketing approach works just as well in reality. "Seeding techniques" are commonly used by certain start-up firms, in which they first give a discounted pricing to their target customers in order to encourage the spread of their product or service. If the firms are operating normally, they may be able to offer regular or even higher pricing after this. There are two factors that require consideration when it comes to sequential dynamic pricing, which is when data is offered to consumers and when the rates are offered. The short-term (immediate) congestion may become the long-term (permanent) congestion if the demand for social media services increases. "Recovery time" is needed if the server is under a lot of stress in the current time period, for example. Servers can't keep up with demand since they have little time to recuperate. Due to previous networking activities' congestion, this might have an impact on the following activities, as well Long-term congestion in which data use for service access in previous time periods might still generate congestion in succeeding time periods is the focus of this research. Research in this area should focus on a short-term congestion model in which overall data use does not influence congestion experience in one time period. In this paper, we present a sequential dynamic pricing system in which the social data demand decision of users reacts on various time scales. With the goal of better understanding how consumers pick their tactics simultaneously, we are looking at a simultaneous pricing strategy. The MNO sets the price at the start of each time period under the simultaneous dynamic pricing system. In this way, mobile users may concurrently decide on their own personal social data needs while also taking into consideration the network effects in the social domain and the congestion effects in the network domain.

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

In this part, we run the simulations to show how various factors affect the dynamic pricing schemes. The Erd os-R'enyi (ER) graph is used to model the social features of the graph G. Probability Pe is the same for any social link between any two ER members. According on Brightkite's genuine data trail [20], we also replicate the real social network [21]. Mobile phone users are the primary focus of Brightkite's online social networking service. In order to build the social network, we randomly choose N users from the actual dataset, which might be 10; 15; or 50. The average results of 500 runs are calculated for each number of users, N. One can see how many social relationships and how likely they are to be formed in the actual dataset in Figure 1. Figures 2 and 3 show that sequential dynamic pricing (SeqDP) may be assured during the first 40 time periods in terms of MNO income and overall user utility. The individual utility of two randomly chosen consumers, under SeqDP with and without social fairness consideration, is presented in Fig. 4. SeqDP's ability to provide social justice in terms of individual network utility may be shown by this example. Our suggested SeqDP is compared to OSP income and overall utility in Figure 5-6 to see how the MNO may benefit from social data demand and how much money it will bring in. Additionally, we examine the performance when social data demand is not interdependent. All of the connections in this unique situation of our socially aware user utility have zero. ER-based social graph model (so-ER) and the actual dataset, i.e., Brightkite-based social graph model, are also compared in terms of performance (social graph-Brightkite). Fig. 5 shows that the total utility increases with the probability of social edge, and the total utility attained in the proposed SeqDP is significantly bigger than that of OSP when the likelihood of social edge is greater. Total utility rises when the chance of a social edge increases, as more social neighbours are connected to a user and their social data need grows. As a result, the MNO's income from the SeqDP grows as the chance of social edge increases. MNO income is expected to rise as more people get access because of the network effect, which leads to a stronger demand for social data. ER-based social network model with zero social ties may be used to verify this.

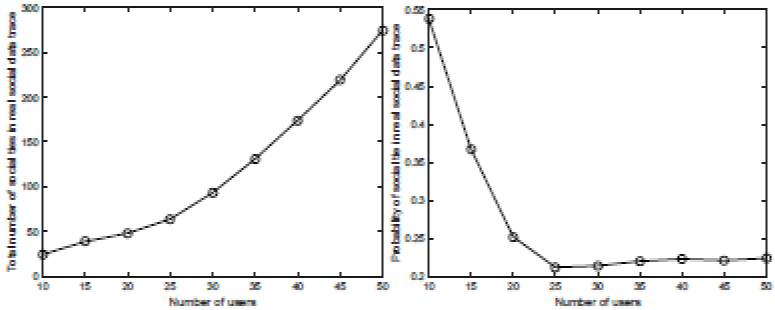

Figure 1. Real social data trace from Brightkite [20]: total number of social ties versus the number of users (left), and probability of social tie versus the number of users (right).

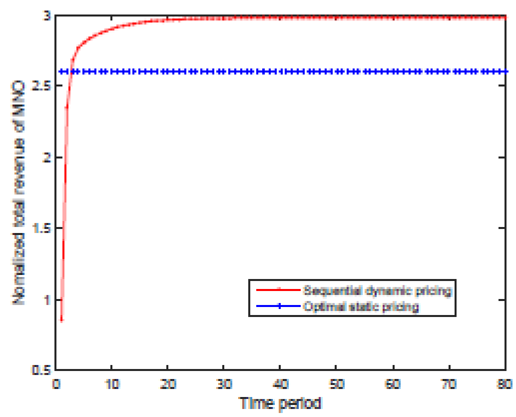

Figure 2. Normalized total revenue of the MNO versus time periods.

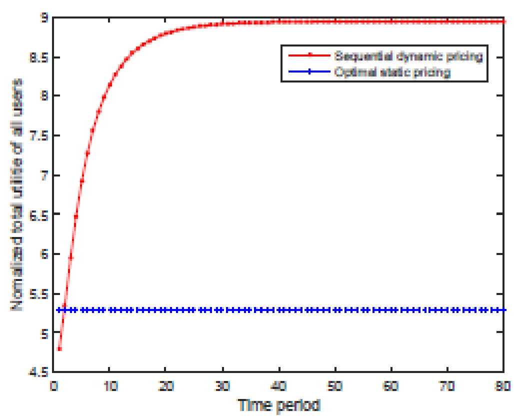

Figure 3. Normalized total utilities of mobile users versus time periods.

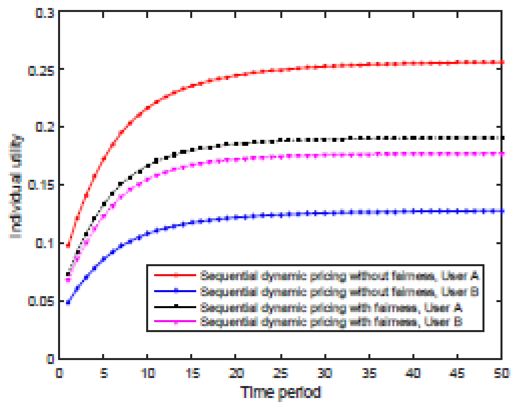

Figure 4. The illustration of individual utility of users with and without social fairness consideration.

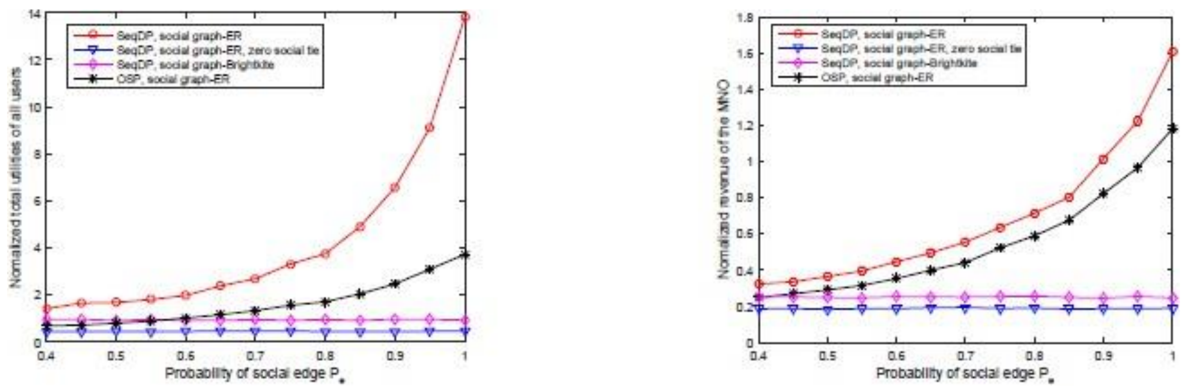

Figure 5. Normalized total utilities of users and normalized revenue of the MNO versus the probability of social edge.

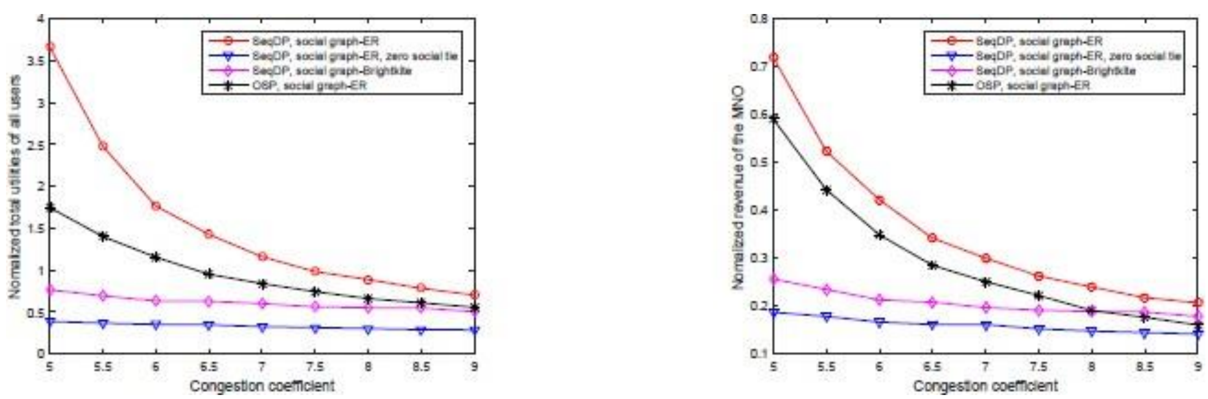

Figure 6. Normalized total utilities of users and normalized revenue of the MNO versus the congestion coefficient.

CONCLUSION

Using dynamic pricing methods in the mobile social data market, we have proposed a revenue maximisation approach. An individual fee for social data access is offered to each user sequentially and repeatedly by the network operator under a sequential dynamic pricing plan. The suggested pricing model has taken into account both the social and network implications of congestion. Extensive testing has been done using Erd os-R'enyi graphs and actual dataset-based social networks to verify that pricing scheme dynamics are better. Machine learning will be used in future research to discover the parameter values that are most closely aligned with the actual data market, allowing us to more intelligently and precisely forecast demand for our services. It is possible that various time periods have distinct network impacts and congestion coefficients. As a result, we want to investigate how to anticipate the values of parameters in a dynamic mobile social data marketplace. Another intriguing path is to investigate the theoretical findings' sensitivity. Aside from that, we'll be extending the utility formulation of users to include the network and congestion impact components.

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