Application-Oriented Free Data in Cellular Networks

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ABSTRACT Over the past several years, sponsored mobile data and the payment directions on the Internet have been two major subjects in network economics. Several tier-1 service providers (SPs) created their frameworks for sponsored mobile data by cooperating with content providers. Based on these frameworks, users can have free data transfer if they accomplish a predefined task such as watching advertised videos. In this paper, we investigate particular types of mobile applications that can deliver their data to all cellular users free, even to the users without a data plan. Our approach does not force users to click on advertised content to obtain free data access yet it can still generate a level of revenue for application providers (APs) that can compensate for the revenue loss of the network service provider. We call this approach an Application-Oriented Free Data (AFD) program. To model and analyze the characteristics of the considered framework we use a multi-stage game consisting of cellular users, an SP, and an AP. We solve this game by backward induction. In this way, we define the required thresholds of price and data usage for an AFD program. The feasibility of the AFD program is illustrated by several numerical examples.

INDEX TERMS Cellular data service, network economics, net neutrality, sponsored data, content-aware networks, free cellular data, Google Maps.

I. INTRODUCTION

The circuit-switched networks have no knowledge about the transmitted information or its worth and hence the dominant type of pricing for these networks is based on the duration of each connection. With the introduction of packet-switched networks, the network service providers (SPs) could introduce the second type of pricing that is based on the volume of transferred data. Analyzing volume-based pricing schemes was the subject of our recent work [1], [2]. Note that in the volume-based pricing there is no resolution among different types of data, but this can change soon due to the vast implementation of content delivery networks (CDN) [3] and edge-computing. These developments lead to many studies of content-aware networks (CAN), e.g. [4] and [5],

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and wide implementation of CAN networks is expected in near future Internet. The arrival of CDN networks creates new opportunities for customizations and improvements of the current pricing policies that would have an eye on fairness and user satisfaction. This context gives us the motivation to focus in this paper on an economical framework and models where specific mobile applications have no cost to the end-users. In these cases, the network service providers (SPs) and eligible application providers (APs) cooperate to leverage the natural behavior of users, such as online shopping, to generate revenue.

In the proposed approach, the users are not forced to click on advertised contents in order to obtain free data transfer but it should be underlined that this is possible only for eligible types of applications. In particular, applications such as mapping services with embedded advertising capability for local businesses are the best candidates for our method

but, for example, the data transfer for video streaming apps with high demand cannot be offered free for all users without experiencing revenue loss. Hence, we call our approach an Application-Oriented Free Data (AFD) program. The economic framework of the AFD program is different from the classical sponsored data method in which the sponsored content is selected by a content provider and it can be a specific video or music. It is also different from recent methods in which users obtain free usage by participating in selected activities such as clicking on online ads. We focus on the entire data generated by an eligible application and prove that it can be offered to all users free of charge and restrictions on usage. We prove that any application that meets eligibility criteria can join the AFD program. Hence, it does not affect the APs that are competing and provide similar content types through their applications. One example of an eligible application type is mapping services that have small data usages and generate their revenue from local businesses. These businesses can be hotels, shopping centers and any market relying on the online advertisement. The second example of an eligible application type is real-time IoT services like health monitoring wearable devices connected to cloud-based applications. These applications usually use small amounts of data transfer, yet carry high-value information that is processed and billed by third-party cloud-based services. In Section III, we show the business models of different types of eligible applications and elaborate on their differences. However, in all of them, the payment directions under the AFD program are similar to the ones shown in Fig. 1, where users do not pay for the data transfer associated with the eligible applicants. We show that even with a linear relation between data usage and revenue of AP and with maximum usage of the eligible application by all users, the AP can compensate for the revenue loss of the SP in an AFD program.

In this paper, we consider the economic interactions between three network entities. Namely, an AP, an SP, and users. The data usage behavior of the SP's subscribers is modeled with a utility function that is in harmony with real network statistics. The SP has a contract with each user that is charged based on its usage excluding the usage under the AFD program. The AP offers a free application to all users and it makes revenue by showing advertisements or information provided by third-party local businesses. We show that the AP can compensate for the profit loss to the SP. In particular, we model this process as a two-person bargaining problem and find its Nash Bargaining solution. Our model identifies the threshold of the bargaining power of SP when the AFD program is possible. We also prove that all APs with eligible applications are better off with the AFD program if their profit model is at least in linear relation with consumed data.

The rest of this paper is organized as follows. Section II is dedicated to the related work. In Section III, we introduce two categories of applications that are candidates for the AFD program. In Section IV, the sequential game for the first category of applications is developed and analyzed
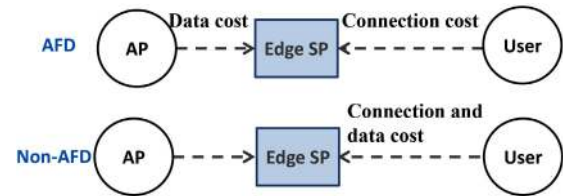

FIGURE 1. The payment directions for AFD and Non-AFD apps.

(we selected for analyzing the first category due to its higher complexity). Section V includes numerical examples. Finally Section VI concludes the paper.

II. RELATED WORK

To have a deeper understanding of the AFD program, we explain several industrial and academic endeavors toward partially free data access. From the industrial side, one of the first mechanisms was sponsored data option introduced by AT&T [6]. In this approach, users can have free data access for sponsored content, besides their regular data plan. One example is sponsored videos that are provided by content providers (CPs) approved by AT&T. If users watch such videos, there is no impact on the usage of their regular data plan. T-Mobile and Verizon also introduced Binge On [7] and FreeBee [8], respectively. They both follow philosophy similar to the one used in AT&T's plan with several differences in detail. The key to all of these plans is the presence of CPs who are eager to sponsor free data transfer. Due to the required sponsorship, the offered free content is restricted to specific CPs and moreover, to the selected content that CP sponsors. Also, these plans are offered to the users who already have a data plan which is a major drawback regarding fairness and social welfare. Another concern about the sponsored data program is the violation of network neutrality. Since the major SPs can attract powerful CPs by charging them for their access to the end-users, the smaller CPs and SPs cannot compete in this field and that is in contradiction to widely accepted practice which suggests an equal and neutral policy for all data over the Internet.

Concerning the net neutrality itself, [9] analyzes the short-term effect of net neutrality in a monopoly market. This work investigates different rules of neutrality and shows that the strict net neutrality that includes a single transport class is not socially efficient due to traffic inflation. The authors argue that by deviation from net neutrality, a socially optimal traffic allocation can be achieved. The authors of [10] consider two competing Internet providers and a group of content providers. They study the effect of net neutrality on investment for capacity expansion and also on content innovation. They suggest that under a discriminatory regime in which the platforms charge priority fees for faster content delivery, the capacity investment and innovation are higher than in the case with net neutrality. Reference [11] investigates the profitability of non-neutral networks and shows that in certain scenarios, a non-neutral network is nonprofitable.

Also, it shows that when the market power of an SP is small, the end-users can obtain a better overall payoff in a non-neutral regime. Reference [12] analyses the interaction between a CP and an SP when the SP agrees to offer a better QoS to CP's service. This can be seen as a coalition of the two providers which is achieved by an agreement in a bargaining game. The effect of bargaining power on the QoS and the social efficiency level are the two factors that are considered in this work. Reference [13] investigates the optimum amount of content that the CP should sponsor. It shows that with sponsored data applied, the utility of users increases more than the utility of CPs. Reference [14] considers a case in which an SP proposes a sponsored data service to several CPs. In this case, the SP aims to select one of the CPs for the offered service and to determine the service price that maximizes its revenue. One of the main issues that is addressed in [14] is the truthfulness of CPs when they report their network parameters. In [15], authors consider a market with a monopolist mobile network provider and two competing content providers. The data usage of users and their preference for CP selection are heterogeneous. The authors found that the optimal pricing scheme in the mentioned network settings is a two-part tariff without any data cap. Reference [16] models the interaction between CP-SP as a two-stage Stackelberg game where the CP and SP are leaders and the users are followers. It considers two cases: competitive and cooperative. In the competitive case, each provider tries to maximize its own profit. In the cooperative case, CP and SP jointly optimize their strategies. Reference [17] studies the concept of sponsored data and models the interaction between CP, SP, and users as a three-stage game. The authors derive the model for content demand for users and the best-sponsoring strategy for CP. This study proves that the revenue levels of CP and SP and utilities of users are improved under the sponsored content policy. The authors of [18] analyze a sponsored content/service market with a two-stage Stackelberg model. The service selection strategy of users is modeled as an evolutionary population sub-game. The sponsoring-pricing interaction between CP and SP is modeled as a non-cooperative sub-game. The authors prove the existence of equilibrium and propose an iterative algorithm to find it. There are also several works that study the cooperation between network entities and network economics, e.g. [19]–[22].

The main difference between our work and the mentioned studies, specially [16]–[18], is the type of sponsored content that is analyzed in our work. As we explain throughout the paper, AFD eligible applications have a very small usage pattern but are highly important to the end-users according to real-world statistics. They also have in-app business models which generate the revenue from the local businesses and third parties instead of regular end-users of the application. This combination motivates the SP and CPs to cooperate and achieve a common ground to offer such apps free of charge. To the best of our knowledge, the full sponsorship model proposed in our paper was not addressed in the previous studies. Also note that in our paper, we consider AP-SP models instead of studying the CP-SP interaction. The advantage of this approach is that we can take advantage of particular features of the content provided by an application while in general, a content provider offers many contents that are often controlled by independent application providers.

III. ON THE FEASIBILITY OF AFD PROGRAM

In this section, we focus on those types of applications that can be offered free of charge to the end-users. We define two categories of the eligible applications and their common characteristics.

A. CATEGORY 1: MAPPING APPLICATIONS

The data acquired from comScore's 2016 report [23] shows that Facebook, Facebook Messenger, YouTube, Google Maps and Google Play are the top five mobile applications. On top of the list is Facebook having 80% of the audience. The Facebook application is known for its moderate to high data usage. The second rank is Facebook Messenger which is less traffic greedy. However, its overall consumption can be very high since it can be used repeatedly during a short time period as a messaging service. The third most reached application is YouTube which generates the most traffic when compared with other applications in the list. Based on YouTube's statistics, the average viewing session for mobiles is 40 minutes as of 2016 [24]. This means for 480P videos, having 2.5 Mbps data rate, YouTube consumes 750 MB per average session. The fourth most reached application is Google Maps with around 55% of reachability in the U.S market. From the AFD viewpoint, Google Maps has three interesting features comparing to the top three applications. First, it is not a social media application or entertainment service. Hence, every time a user opens this application, it is due to the importance of information that is required. Second, while the first three applications in the list have moderate to high traffic demand, the amount of required data transfer for Google Maps is negligible per request; as of today, based on our measurements, it uses 300-500 KB to process each location request. The final aspect is the new feature of Promoted Pins that lets local businesses offer different kinds of promotions to their customers. The advertisements appear as pins on the map when a user searches for a related location. For example, when a user requests for nearby restaurants, the special offers would appear. Google Maps also supports the bidding mechanisms for hotels. In all of these cases, Google highly relies on its reachability to the users that is directly related to the number of data subscribers in local cellular networks. However, as the data acquired from Ericsson Mobility report [25] in Table 1 shows, over 35% of wireless users in advance markets have a data cap of less than 100 MB. The total traffic generated by this group is 0.7% of total traffic. The traffic share for the group of 100 MB- 1 GB plans is about 11.5% while this group includes 29% of all subscribers. Thus, while Google requires high connectivity of users for its business model, near 64% of subscribers do not have the necessary data connection
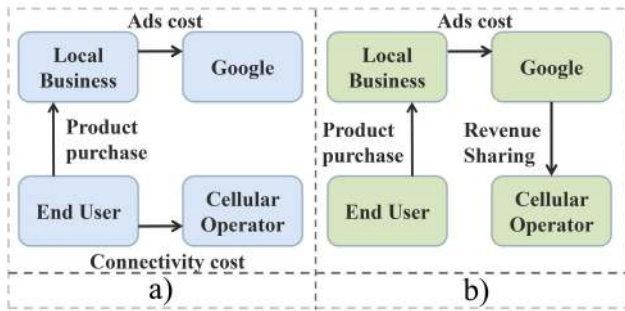
FIGURE 2. a) Traditional payment direction for Google Maps. b) The alternative AFD concept.

FIGURE 3. a) Current payment directions for cloud-cellular IoT applications. b) alternative AFD model.

to use Google Maps freely. The features mentioned above indicate that mapping applications such as Google Maps have the potential to be offered under the AFD program. The traditional payment directions for Google Maps are depicted in Fig. 2-a. Here the end-users pay for their data connectivity, local businesses pay Google for advertisement, and finally, the end-users may pay local businesses for their offers on the mapping application. Under the AFD program, the payment directions would be defined as shown in Fig. 2-b. In this case, the end-users do not pay for their usage of Google Maps. Instead, the content-aware cellular network allows them to use this application free of charge. To compensate for the SP's lost revenue from the end-users, Google would share part of its extra revenue with the SPs. The extra revenue comes from the increased advertisement clicks which are due to the higher service usage by the SP's users. Note that this alternative scenario is feasible due to some unique characteristics of Google Maps. We will further discuss these characteristics in Section III-C.

B. CATEGORY 2: REAL-TIME CLOUD-BASED IoT APPLICATIONS

The second category of applications eligible for the AFD program is related to the rapid development of wearable devices, IoT applications, and edge-computing. In contrast to the first category in which the end-users would not directly pay for using the applications of Google or Apple, in the second category users pay for the cloud-based applications. In the current market model, the end-users pay for both data connectivity and cloud-based applications that collect event-triggers from sensors and react. However, there are some scenarios in which the current market model can be inefficient or even dangerous. For example, consider a health monitoring system that loses its connection to the cloud-based service when the data plan reaches its cap. In such a scenario, while the user already paid for a critical service, the service cannot save its life. Therefore, this service could benefit greatly from the AFD program and the same applies to a broad range of IoT applications using low data using sensors that provide valuable information. The traditional payment model requires the end-users to pay for both network connectivity
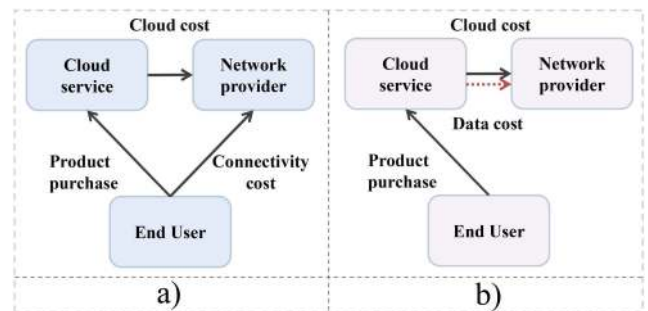
and the cloud-based applications located on the edge of the provider's network. This model of payment directions is depicted in Fig. 3-a. The alternative AFD model removes the data transfer and connectivity cost from the end-user. In this model, the cost of data transfer is being paid by the cloud-based service owner.

C. CHARACTERISTICS OF ELIGIBLE APPLICATIONS FOR THE AFD PROGRAM

Until now we defined two categories of applications that are good candidates for the AFD program. In this Subsection, we define some general characteristics that should be possessed by the eligible applications.

Property 1: let us define the expected content size for each application as the average size of data that is passed to the user when it performs a regular content request such as obtaining a map location from Google Map. Then, in the eligible applications, the expected content size is relatively small and its perceptual value to the user is high. On the other hand, for the content types such as video, the expected size of each video is significantly higher, and the data does not have the same importance or time criticality. In other words, in most cases when a user requires a map location data or health-care service, the request cannot be postponed till another time. This argument is backed by the real data from Ericsson [25] that shows the higher priority of Mapping applications when the monthly plan bandwidth is limited. Let us represent the content size as θ and the perceptual importance to a user as a random variable α. Then, the importance to size ratio is $\rho = \frac{\alpha}{\theta}$. Since the two variables are generally independent, the average ratio is $E[\rho] = \frac{E[\alpha]}{E[\theta]}$. We expect this ratio to be the highest for the eligible applications when compared with all application types in the network. This definition lacks two pieces of important information. First, there is no metric for perceptual importance. Thus, we need to use a utility function to model user behavior. This utility function is presented in Section IV-A. Second, ρ does not carry any information about the user greediness for the application usage which forces us to define the second property.

Property 2: the second property of eligible applications is that the user should not be greedy for the application usage.

TABLE 1. Subscriber and traffic shares in advance mobile markets, adopted from Ericsson mobility report [25].

Size of data plan	< 100 MB	100 MB $- 1$ GB	$1 - 10$ GB	$10 - 100$ GB	> 100 GB
Subscriber share	$\approx 35\%$	28.8%	32%	$\approx 3.5\%$	$\approx 0.7\%$
Traffic share	$\approx 0.7\%$	$\approx 11.5\%$	$\approx 48.2\%$	$\approx 35.2\%$	$\approx 3.5\%$

TABLE 2. Application volume shares of different subscriber groups adopted from Ericsson Mobility report [25].

Application	< 100 MB	100 MB $- 1$ GB	$1 - 10$ GB	$10 - 100$ GB	> 100 GB	All users
Video	4%	16%	39.5%	67%	67.7%	46.7%
Social Networking	13.7%	17.7%	17.7%	6.5%	1.2%	13.7%
Web Browsing	20%	18.5%	12%	5.6%	2.4%	10.4%
Communication Services	12%	8.8%	4%	2.4%	0.8%	3.2%
Software Download	16.1%	15.3%	6.4%	2.4%	1.6%	6.4%
Audio	0.8%	3.2%	3.2%	1.6%	0.8%	3.2%
System	0.2%	1.6%	$\approx 0\%$	$\approx 0\%$	$\approx 0\%$	$\approx 0\%$
File Sharing	$\approx 0\%$	$\approx 0\%$	$\approx 0.5\%$	$\approx 1.6\%$	$\approx 16\%$	1.6%
Other	$\approx 33.2\%$	$\approx 18.9\%$	$\approx 16.7\%$	$\approx 15.3\%$	$\approx 9.5\%$	$\approx 14.8\%$

We define the overall size of data transferred by application a and user j in the period from the beginning of the billing cycle till time t as $\Theta_{j,t}^a(d)$, where d is the cap of user's data plan. Then, the application usage index (AUI) among all users can be defined as,

$$I_j^a(d) = \lim_{t \to \infty} \frac{\Theta_{j,t}^a(d)}{\sum_{a=1}^A \Theta_{j,t}^a(d)}. \qquad (1)$$

For the eligible applications, AUI should decrease with increasing d, and that is stated in the following greediness condition:

$$\frac{1}{N} \sum_{j=1}^N \frac{\partial I_j^a(d)}{\partial d} \leq 0, \qquad (2)$$

where N is the total number of users in the market. For example, consider the Rows 3 and 4 of Table 2 that are related to web browsing and communication services. When users have a small monthly data plan, such as 100 MB, the share of such services in their total usage is 20% and 12% respectively. However, as the data plan increases, their usage share decreases. For users with 1-10 GB of available data, their share is 12% and 4%. This pattern is shown in Fig 4-c and is an exact representation of Equation 2. We can find two other general patterns related to $I(d)$ from the data of Table 2 that are shown in Fig 4-a and Fig 4-b. Fig. 4-a shows the usage index shape for Type-I applications for which users have the highest usage greediness; this type includes the video applications in Table 2. Fig. 4-b illustrates the usage index shape for Type-II applications. A user considers utilizing these applications if it has enough bandwidth available. However, these applications are not important enough to be used in plans with a small data cap. Audio services belong to this category. Finally, 4-c depicts the usage index shape for the critical applications that the user requires under any data plan. A user may utilize only these applications when the data cap is limited to a small value, e.g., one- or two-gigabytes. Also, users are not greedy for these applications so condition (2) is satisfied in this case. Web browsing and mapping applications
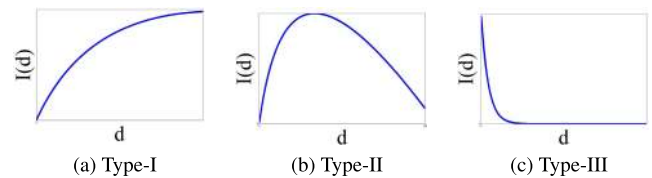

(a) Type-I   (b) Type-II   (c) Type-III

FIGURE 4. Three types of mobile applications based on subscriber's usage behavior defined by $I_u(d)$.

belong to this application type. Being a Type-III application is a necessity to be eligible for the AFD program. However, it is not sufficient; the business model should also support the AFD program. Hence, a third characteristic should be defined to resolve necessity and sufficiency conditions for eligible applications.

Property 3: until now we considered the usage characteristics of eligible applications. The third characteristic is related to the market condition. For any service to be considered as AFD eligible, there should be a business or a social entity that can compensate for the revenue loss of cellular providers. This characteristic may look trivial, but when we compare a mapping service with web browsing applications, one can notice a structural difference in the business model. Namely, for mapping applications such as Google Maps, there is an explicit financial loop from local businesses to Google, to SPs, to users, and again to local businesses. On the other hand, there is no such loop for browsing applications since the potential gainers are distributed throughout the Internet. The only exception would be injecting direct advertisement from cellular provider to the web browsing data and making a payment loop similar to Google Map's business model in Fig. 2-a.

Among the two categories of eligible applicants for the AFD program, the first category has the most complicated structure. It includes users, SPs and APs that directly affect each other behavior. The AFD feasibility models for the Category 2 and 3 applications are simpler and can be derived by some modification of the first category model. We studied
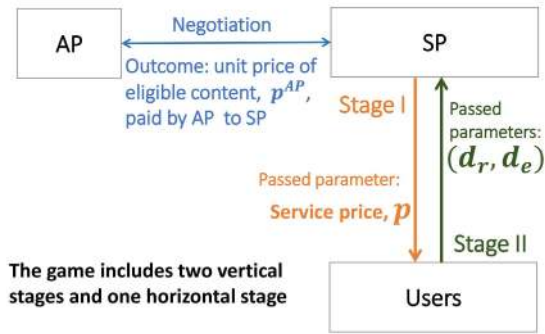
the Category 3 applications in [26]. Hence, in the remainder of the paper, we propose and analyze a detailed analytical model for the AFD feasibility of the Category 1 applications.

IV. THE GAME FOR CATEGORY 1 APPLICATIONS

In this section, we consider a three-stage game that defines the best strategies of SPs and APs for joining or refusing the AFD program for an eligible Category 1 application. The game consists of three entities: cellular users, an SP, and an AP. Users adjust their subscription and data usage behavior based on the offered plan prices from the SP. The AP generates its revenue based on the number of subscribed users and the amount of data requests they generate. Similar to any market, since the volume of data requests is in close relation to the unit data price offered by the SP, the AP earns an extra revenue if the SP applies the minimum possible price. Our goal is to investigate and define the conditions in which an entirely free access gives a sufficient amount of extra revenue to the AP to compensate for the revenue loss of SP. We model the interaction between SP and users as a two-stage Stackelberg game and solve it by backward induction. Then, the negotiation between AP and SP is modeled via the Nash bargaining solution (NBS). Fig. 5 shows the general structure of the game.

In the following Subsection A, we analyze the best demand response of the mobile subscribers assuming that the service price of SP is known. This is the second stage in our Stackelberg game. Then, in Subsection B, the optimal service price of SP is modeled in the first stage of the game. Subsections C and D are dedicated to the optimal prices of SP related to its non-cooperative and cooperative strategies, respectively. Subsections E, F and G are dedicated to the negotiation stage. Subsection E discusses the possibility of AFD program from the AP's point of view while Subsections F and G present the revenue of AP based on its bargaining power over SP using the Nash bargaining solution and Shapley value, respectively.

A. STAGE II: USER's UTILITY AND BEST RESPONSE
Since user behavior analysis is the foundation of the proposed framework, we need to define the proper metric to find the amount of data consumption. Similar to many related works, we use the concepts from utility theory to formulate this

metric. With the help of the data provided by Ericsson [25] in Tables 1 and 2, we know that 70% of current users have a limited data plan with less than 2 GB; the primary concern of these users is choosing between high priority data provided by mapping applications and other less critical data such as video. For these users, the utilization percentage of high demanding applications such as video is negligible. For the rest of users who share almost 80% of overall traffic, the decision concern is mainly about the amount of traffic they need to buy for their video streaming applications. For these users, the traffic ratio of high-value applications to the rest of applications is under 10% (Type-III applications in Fig. 4). Hence, we can define a two-part utility function that considers the importance of eligible application in one part and the importance of high demand applications in the other part. For each part, we use the familiar form of logarithmic utility function due to its conformity to the *law of diminishing marginal utility* [27]. The adoption of this law is essential in studying cases of data consumption. Also, the logarithmic utility is a common practice in related works e.g. [28] and [29]. The utility for a specific user j has the form of:

$$u^j(p) = \frac{\alpha_e^j \beta_e log(1 + d_e^j) - p d_e^j}{U_e}$$
$$+ \frac{\alpha_r^j \beta_r log(1 + d_r^j) - p d_r^j}{U_r}. \quad (3)$$

The first part of the above function defines the gained normalized payoff from using an AFD eligible application. This application is indicated by subscript e. The second part belongs to the rest of the applications with lower importance and higher traffic demand indicated by index r. We define α_i^j, $i \in \{e, r\}$ as a random variable which shows the importance of the application i to user j. This importance is coupled with the amount of money that the user is willing to pay for a specific type of application. For the sake of simplicity in analysis, we assume that α_e^j and α_r^j are i.i.d having a uniform PDF of $U(0, 1)$. Note that it is highly common to use a uniform valuation in economic analysis. We refer the readers to [30] and [31] as two well-known examples. β_i is a user-independent variable that controls the amount of data consumption for a given price. d_i^j is the amount of preferred data usage for each application type. We also define constant D_i which indicates the maximum amount of data consumption users tend to achieve. Based on the definition, we expect D_e to be negligible comparing to D_r. $p \in \Re^+$ is the unit price for data implied by the SP. Finally, U_e and U_r are the normalizing factors which control the peak of utility for each application. These two constants are essential since the two parts of utility have different peaks, yet they may represent the same amount of satisfaction to each user. By this definition, $U_i = \beta_i log(1 + D_i)$ and the maximum of $u^j(p)$ for the most demanding user can be 2. For the rest of users, the maximum utility is $u_M^j(p) = \alpha_e^j + \alpha_r^j < 2$ which shows that the maximum value of satisfaction is related to the perceptual importance of the applications to the user. It is

clear that $u^j(p)$ is concave with respect to d_e^j and d_r^j. The first derivative of $u^j(p)$ with respect to d_i^j is:

$$\frac{\partial u^j(p)}{\partial d_i^j} = \frac{1}{U_i}\left(\frac{\alpha_i^j \beta_i}{1 + d_i^j} - p\right), \tag{4}$$

$$d_i^{j'} = \frac{\alpha_i^j \beta_i}{p} - 1, \tag{5}$$

where $d_i^{j'}$ is the global maximum of $u^j(p)$. By considering the positivity and the maximum level of usage, we have the optimum value as:

$$d_i^{j^o} = \min\left(\max\left(\frac{\alpha_i^j \beta_i}{p} - 1, 0\right), D_i\right). \tag{6}$$

The above equation indicates that $p \geq \alpha_i^j \beta_i$ leads to zero usage for the application of type i, and $p \leq \frac{\alpha_i^j \beta_i}{1+D_i}$ gives the user the opportunity to reach the maximum demand for the application of type i. To have the analysis of the user's best responses, we need to categorize the users based on usage threshold orders. These orders can be represented by two main sets:

Order set I-
$$\begin{cases} 1) & \alpha_e^j \beta_e \geq \alpha_r^j \beta_r > \dfrac{\alpha_e^j \beta_e}{1 + D_e} > \dfrac{\alpha_r^j \beta_r}{1 + D_r}, \\[2ex] 2) & \alpha_e^j \beta_e > \dfrac{\alpha_e^j \beta_e}{1 + D_e} > \alpha_r^j \beta_r > \dfrac{\alpha_r^j \beta_r}{1 + D_r}. \end{cases} \tag{7}$$

Order set II-
$$\begin{cases} 3) & \alpha_r^j \beta_r > \alpha_e^j \beta_e > \dfrac{\alpha_e^j \beta_e}{1 + D_e} > \dfrac{\alpha_r^j \beta_r}{1 + D_r}, \\[2ex] 4) & \alpha_r^j \beta_r > \alpha_e^j \beta_e > \dfrac{\alpha_r^j \beta_r}{1 + D_r} > \dfrac{\alpha_e^j \beta_e}{1 + D_e}, \\[2ex] 5) & \alpha_r^j \beta_r > \dfrac{\alpha_r^j \beta_r}{1 + D_r} > \alpha_e^j \beta_e > \dfrac{\alpha_e^j \beta_e}{1 + D_e}. \end{cases} \tag{8}$$

The main difference between the two sets is the user's application prioritizing behavior. The first set represents the users who prioritize the type e applications and the second set is for the users who favor the type r applications. To have a better understanding of the user behavior, let us define the best response function as follows:

Proposition 1: The best response data values for the users in the first order (set I-1) are as follows:

$$\text{I-1} \begin{cases} d_e^{j^o} = 0, \, d_r^{j^o} = 0 & p > \alpha_e^j \beta_e, \\[2ex] d_e^{j^o} = \dfrac{\alpha_e^j \beta_e}{p} - 1, \, d_r^{j^o} = 0 & \alpha_r^j \beta_r < p \leq \alpha_e^j \beta_e, \\[2ex] d_e^{j^o} = \dfrac{\alpha_e^j \beta_e}{p} - 1, \, d_r^{j^o} = \dfrac{\alpha_r^j \beta_r - p}{p} & \dfrac{\alpha_e^j \beta_e}{1+D_e} < p \leq \alpha_r^j \beta_r, \\[2ex] d_e^{j^o} = D_e, \, d_r^{j^o} = \dfrac{\alpha_r^j \beta_r - p}{p} & \dfrac{\alpha_r^j \beta_r}{1+D_r} < p \leq \dfrac{\alpha_e^j \beta_e}{1+D_e}, \\[2ex] d_e^{j^o} = D_e, \, d_r^{j^o} = D_r & p \leq \dfrac{\alpha_r^j \beta_r}{1+D_r}. \end{cases} \tag{9}$$

Proof: The thresholds come directly from (7) and the optimum values follow (6). $\square$

The best response for the rest of the threshold orders can be easily defined based on the above definition. We omit their discussion to simplify the presentation. Instead, we show the typical curves of best responses for the threshold orders in Fig. 6 (next page). As depicted in Fig. 6(a)-(e), the main difference between the best response curves is the usage behavior when the price is high. Sub-figures 6-(a) and (b) represent the users who prioritize the eligible applications over the rest of the applications. Hence, when the price is high, they use only the eligible applicants. This makes a significant difference in the AUI curve. The single-user AUI of the eligible application, $I_e(p) = \frac{d_e(p)}{d_e(p)+d_r(p)}$, for the first two orders is similar to the one of the Type-III applications (a horizontally flipped version of the curve in Fig. 4, having d inversely related to p). Order II-1 shows a pattern similar to the Type-II applications for the presumably eligible applications. Orders II-2 and II-3 represent our eligible applications similar to the Type-I applications. Based on the three characteristics of the eligible applications for the AFD program, we know that only Orders I-1 and I-2 are a realistic representation. This assertion does not imply that all users act based on the first two orders. However, since the marketwide AUI (Eq. (1)) represents the aggregated usage of an application in the entire market when it comes to an eligible application the majority of users behave based on Orders I-1 and I-2. Hence we can propose the following proposition:

Proposition 2: For an eligible Category 1 application, $\beta_e > \beta_r$ always holds.

Proof: See appendix A. $\square$

B. STAGE I: THE BEST STRATEGY FOR SP

In Stage II, after the analysis of users' best responses, the SP should determine its best strategy. As discussed earlier, the SP decides whether it wants to participate in the AFD program or not and also sets the data price that maximizes its revenue. Thus, the strategy of SP is defined by triple (p, γ^{SP}, p^{AP}) where p is the data unit price for type r applications, $\gamma^{SP} \in \{0, 1\}$ defines the participation strategy and p^{AP} is the data unit price for the type e application when the SP participates in the AFD program, $\gamma^{SP} = 1$. p^{AP} is the base for any payment from the AP to the SP to compensate for the SP's revenue loss. In the following, we derive the optimum revenue values for each strategy triple.

The revenue of SP, when it does not participate in the AFD program, is directly related to the overall data consumed by the subscribed users. When the SP agrees to join the AFD program, it loses a part of its revenue which comes from the eligible application's traffic. However, in the considered scenario, the AP compensates for the revenue loss of SP by making a side-payment. Thus, having N as the total number of users in the SP's network, we can define the revenue
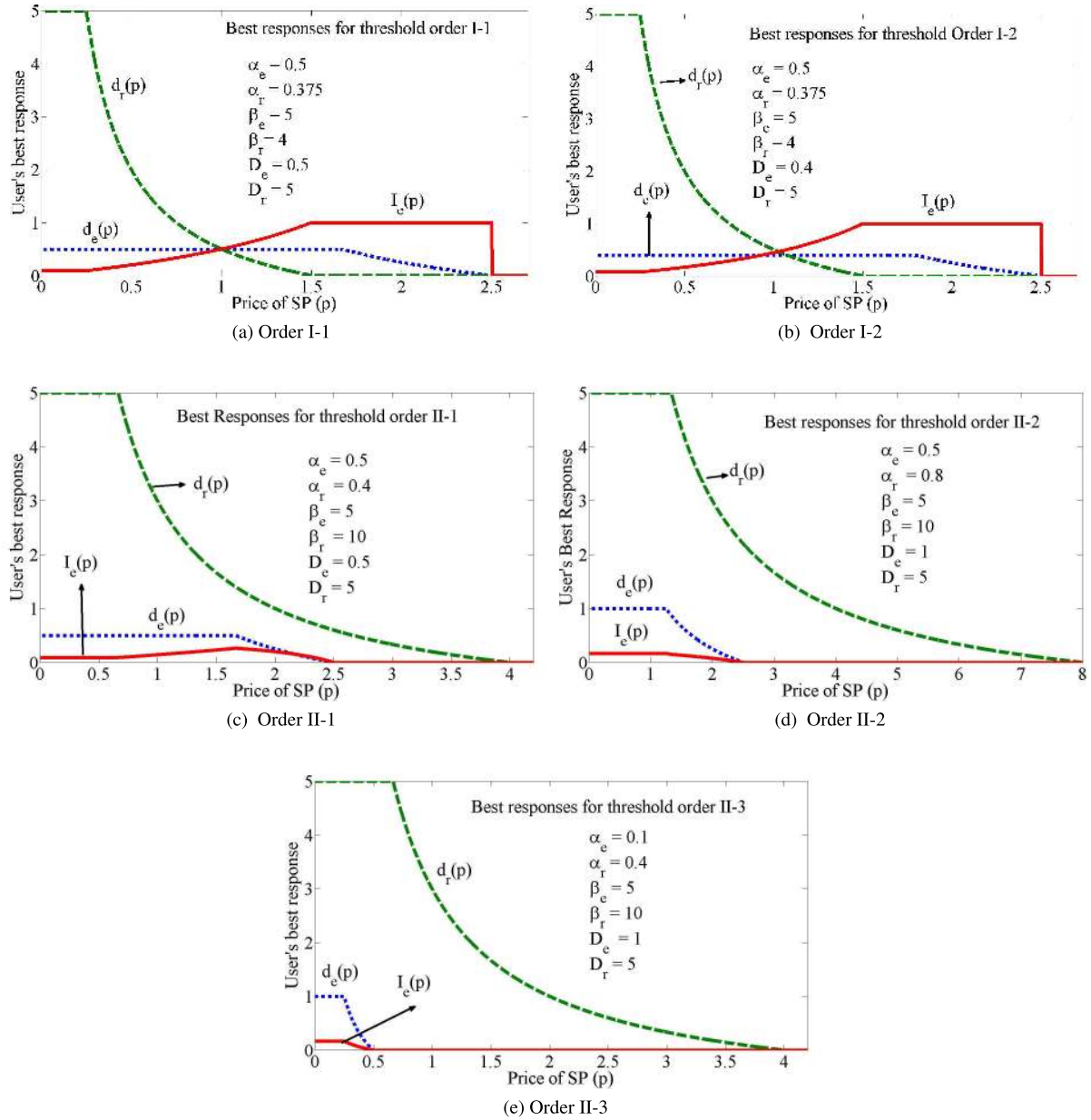
FIGURE 6. Best response of users base on threshold orders.

function of SP as:

$$\pi^{SP}(\gamma^{SP} = 0, p) = N \times \left[\int_{\alpha_e=1}^{1} d_e(\alpha_e, p) d\alpha_e \right.$$
$$\left. + \int_{\alpha_r=1}^{1} d_r(\alpha_r, p) d\alpha_r \right], \quad (10)$$

$$\pi^{SP}(\gamma^{SP} = 1, p, p^{AP}) = N \left[\int_{\alpha_r=1}^{1} d_r(\alpha_r, p) d\alpha_r \right.$$
$$\left. + D_e p^{AP} \right]. \quad (11)$$

Eq. (10) represents the non-AFD revenue and (11) is the revenue of SP under the AFD program. In (11) the side-payment

from AP to SP it is defined as $ND_e p^{AP}$ that implies that under the AFD program, in which users are not charged for transferring type e applications, all users reach maximum usage D_e. Based on the above revenue equations, we define a detailed revenue structure of SP based on its pricing and participation strategies in the following two subsections.

C. THE REVENUE OF SP IN NON-COOPERATIVE STRATEGY ($\gamma^{SP} = 0$)

When the SP is not engaged in the AFD program, its only source of revenue is the direct payments from the users for their data usage. In this case, the SP should set the price value that maximizes its revenue. Based on (6), the price threshold
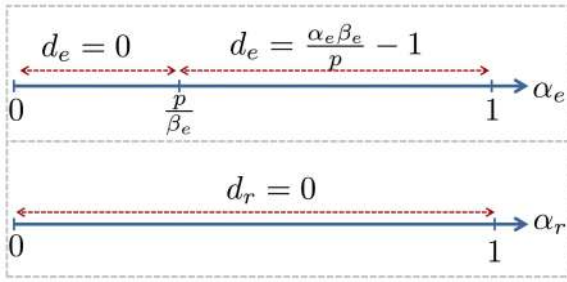
FIGURE 7. Optimal data usage with respect to α_e and α_r in ultra-high price regime $\beta_r < p < \beta_e$.
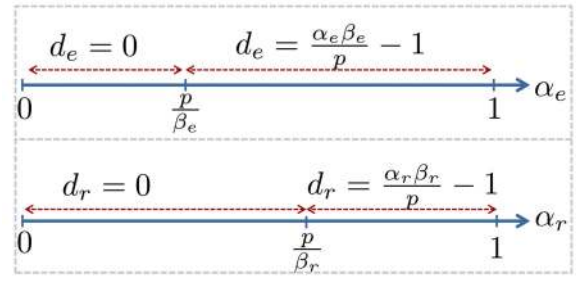

FIGURE 8. Optimal data usage with respect to α_e and α_r in high price regime $\frac{\beta_e}{1+D_e} < p < \beta_r$.

above which user j does not demand any data from application i is $p = \alpha_i^j \beta_i$. Hence, if the SP sets the price $p > \beta_i$, no user would demand data from application type i. We have two thresholds $p = \beta_e$ and $p = \beta_r$ representing the upper limit of the price for each application type. Also, for the same user j, $p <= \frac{\alpha_j^i \beta_i}{1+D_i}$ leads to maximum data usage. We can take the thresholds $p = \frac{\beta_i}{1+D_i}$ and $p = \frac{\beta_r}{1+D_r}$ as the price values for which greediest users start to enjoy full data usage for the respective application. Based on the above definitions and Proposition 2, there are two orders of thresholds:

$$\begin{cases} 1)\ \beta_e > \beta_r \geq \frac{\beta_e}{1+De} > \frac{\beta_r}{1+Dr}, \\ 2)\ \beta_e > \frac{\beta_e}{1+De} \geq \beta_r > \frac{\beta_r}{1+Dr}. \end{cases} \quad (12)$$

The above orders can also be derived from Order set I in (7). We select the first order as the base for further analysis since the same approach can be applied to the wireless markets with the second order. We define the SP's best response price and the associated revenue under each price regime as follows:

1) ULTRA-HIGH PRICE REGIME: $\beta_r < p < \beta_e$
When the SP applies an ultra-high price regime, no user reach its maximum usage regarding application type e. However, as it is depicted in Fig. 7, all the users with $\alpha_e \geq \frac{p}{\beta_e}$ can enjoy a partial usage of $d_e = \frac{\alpha_e \beta_e}{p} - 1$. Considering the type r applications, since p is above the minimal usage threshold, no user will utilize these applications and hence $d_r = 0$ for all the users. The overall revenue of SP is:

$$\pi_{uh}^{SP}(\gamma^{SP} = 0, p) = Np \int_{\alpha_e = \frac{p}{\beta_e}}^{1} \frac{\alpha_e \beta_e}{p} - 1\ d\alpha_e$$
$$= N\left(\frac{p^2}{2\beta_e} - p + \frac{\beta_e}{2}\right). \quad (13)$$

The first derivative of above revenue function is $N(\frac{p}{\beta_e} - 1)$ and the second derivative is $\frac{N}{\beta_e}$. Hence, the revenue function in ultra-high price regime is convex and its maximum occurs at the boundary price $p = \beta_r$:

$$\max_p \pi_{uh}^{SP}(\gamma^{SP} = 0, p) = N\left(\frac{\beta_r^2}{2\beta_e} - \beta_r + \frac{\beta_e}{2}\right). \quad (14)$$

2) HIGH PRICE REGIME: $\frac{\beta_e}{1+D_e} < p < \beta_r$
Considering the user's best responses, the difference between the ultra-high and high price regimes is that in the latter, a part of users with $\alpha_r \geq \frac{p}{\beta_r}$ utilize the type r applications. The best response for the type e application remains the same. This behavior is depicted in Fig. 8.

$$\pi_h^{SP}(\gamma^{SP} = 0, p) = Np\left[\int_{\alpha_e = \frac{p}{\beta_e}}^{1} \frac{\alpha_e \beta_e}{p} - 1\ d\alpha_e \right.$$
$$\left. + \int_{\alpha_r = \frac{p}{\beta_r}}^{1} \frac{\alpha_r \beta_r}{p} - 1\ d\alpha_r\right]$$
$$= N\left(\frac{p^2(\beta_e + \beta_r)}{2\beta_e \beta_r} - 2p + \frac{\beta_e + \beta_r}{2}\right). \quad (15)$$

The revenue function of (15) is convex and similar to (13) and its maximum value is in lower boundary of price $p = \frac{\beta_e}{1+D_e}$:

$$\max_p \pi_h^{SP}(\gamma^{SP} = 0, p) = N\left(\frac{\beta_e + \beta_r}{2}\left(\frac{\beta_e}{\beta_r(1+D_e)^2} + 1\right) - 2\frac{\beta_e}{1+D_e}\right). \quad (16)$$

3) MODERATE PRICE REGIME: $\frac{\beta_r}{1+D_r} < p \leq \frac{\beta_e}{1+D_e}$
In the moderate price regime, the SP allows a part of users with $\alpha_e \geq \frac{p(1+D_e)}{\beta_e}$ reach their maximal usage for application e. However, with such a price regime no user is willing to achieve maximum usage for application r. These conditions are shown in Fig. 9. The revenue of SP in a moderate price regime is defined as shown in (17), as shown at the bottom of the next page.

Proposition 3: The revenue function in moderate price regime has a maximum at $p = \frac{\beta_e \beta_r(D_e-1)}{\beta_r((1+D_e)^2-1)-\beta_e}$, if $D_e > 1$ and $D_r > \frac{D_e(\beta_r(D_e+2)-\beta_e)}{\beta_e(D_e-1)}$, otherwise, the maximum occurs at lower boundary price $p = \frac{\beta_r}{1+D_r}$.
Proof: See Appendix B. □

4) LOW PRICE REGIME: $p \leq \frac{\beta_r}{1+D_r}$
When the low price regime is applied, a part of users achieves the maximum usage for application types e or r or both,
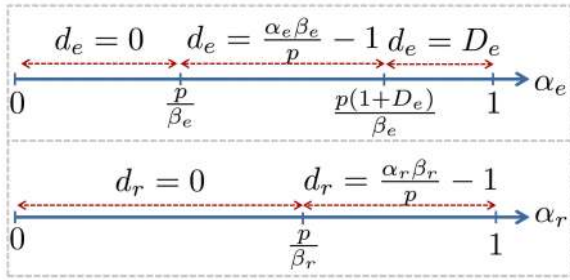
FIGURE 9. Optimal data usage with respect to α_e and α_r in moderate price regime $\frac{\beta_r}{1+D_r} < p \leq \frac{\beta_e}{1+D_e}$.
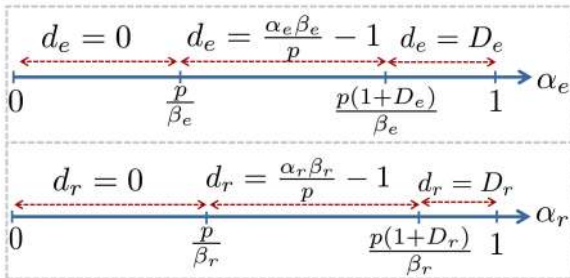

FIGURE 10. Optimal data usage with respect to α_e and α_r in low price regime $p \leq \frac{\beta_r}{1+D_r}$.

as depicted in Fig. 10. The revenue of SP is given by (19), as shown at the bottom of this page. The quadratic revenue function of (19) is concave and the optimal price is given by:

$$p_l = \frac{\beta_e \beta_r (D_e + D_r)}{\beta_e \left((1+D_r)^2 - 1\right) + \beta_r \left((1+D_e)^2 - 1\right)}. \quad (18)$$

Since $D_r \gg 1$, it can be easily proved that $p_l < \frac{\beta_r}{1+D_r}$ and the maximum value of concave revenue function is the optimal value within the price boundary.

The optimal value of p is the one that maximizes the revenue of SP. Since we derived the optimal value for each

pricing regime, the final value can be defined as:

$$\pi_o^{SP}(\gamma^{SP} = 0, p) = \max\left(\max_p \pi_{uh}^{SP}(\gamma^{SP} = 0, p),\right.$$
$$\max_p \pi_h^{SP}(\gamma^{SP} = 0, p),$$
$$\max_p \pi_m^{SP}(\gamma^{SP} = 0, p),$$
$$\left.\max_p \pi_l^{SP}(\gamma^{SP} = 0, p)\right), \quad (20)$$
$$p^o = \operatorname*{argmax}_p \pi_o^{SP}(\gamma^{SP} = 0, p). \quad (21)$$

D. THE REVENUE OF SP IN COOPERATIVE STRATEGY ($\gamma^{SP} = 1$)

In the previous subsection, we analyzed the revenue of SP under the non-cooperative strategy, $\gamma^{SP} = 0$. We categorized the best price responses of SP into four price regimes that yield different usage patterns for application types e and r. Consequently, the revenue values for these regimes vary. If the SP decides not to cooperate, then it selects the price regime that maximizes its revenue. Since the revenue in all price regimes is related to four market parameters β_e, β_r, D_e and D_r, we must adopt a parametric solution for the cooperative strategy of SP as well. In this manner, by considering the application of each price regime to the SP's network, one can derive the cooperative revenue counterpart. We start our analysis by defining user behavior when the SP participates in the AFD program.

When the SP aims to implement the AFD program, users are not charged for demanding data from application type e. The worst scenario for SP is that all users utilize application e to its maximum level of D_e and, simultaneously, no user is willing to raise its data usage from application r. Since the very first condition in the AFD program is the price invariance, the SP loses all the revenue from the application e without obtaining extra value transfer of application r. This condition is previously formulated in (11). One can apply this

$$\pi_m^{SP}(\gamma^{SP} = 0, p) = Np\left[\int_{\alpha_e = \frac{p}{\beta_e}}^{\frac{p(1+D_e)}{\beta_e}} \frac{\alpha_e \beta_e}{p} - 1 \, d\alpha_e + \int_{\alpha_e = \frac{p(1+D_e)}{\beta_e}}^{1} D_e \, d\alpha_e + \int_{\alpha_r = \frac{p}{\beta_r}}^{1} \frac{\alpha_r \beta_r}{p} - 1 \, d\alpha_r\right]$$
$$= N\left(\frac{p^2}{2}\left(\frac{1}{\beta_r} - \frac{1}{\beta_e}\left((1+D_e)^2 - 1\right)\right) + (D_e - 1)p + \frac{\beta_r}{2}\right). \quad (17)$$

$$\pi_l^{SP}(\gamma^{SP} = 0, p) = Np\left[\int_{\alpha_e = \frac{p}{\beta_e}}^{\frac{p(1+D_e)}{\beta_e}} \frac{\alpha_e \beta_e}{p} - 1 \, d\alpha_e + \int_{\alpha_e = \frac{p(1+D_e)}{\beta_e}}^{1} D_e \, d\alpha_e + \int_{\alpha_r = \frac{p}{\beta_r}}^{\frac{p(1+D_r)}{\beta_r}} \frac{\alpha_r \beta_r}{p} - 1 \, d\alpha_r \right.$$
$$\left. + \int_{\alpha_r = \frac{p(1+D_r)}{\beta_r}}^{1} D_r \, d\alpha_r\right]$$
$$= N\left(\frac{-p^2}{2}\left(\frac{1}{\beta_r}\left((1+D_r)^2 - 1\right) + \frac{1}{\beta_e}\left((1+D_e)^2 - 1\right)\right) + (D_e + D_r)p\right). \quad (19)$$

equation to different price regimes to obtain the revenue of SP in the cooperative state. For example:

1) ULTRA HIGH PRICE REGIME: $\beta_r < p < \beta_e$

In the ultra-high price regime, the entire data traffic belongs to application type e. Hence, by participating in the AFD program, the revenue of SP solely comes from the AP as follows:

$$\pi^{SP}(p, \gamma^{SP} = 1, p^{AP}) = N \times D_e \times p^{AP}. \quad (22)$$

It is clear that SP agrees to participate in the AFD program if and only if $\pi^{SP}(p, \gamma^{SP} = 1, p^{AP}) \geq \pi^{SP}(\gamma^{SP} = 0, p)$. Based on (13) and (22), $p^{AP} > \frac{1}{D_e}\left(\frac{\beta_r^2}{2\beta_e} - \beta_r + \frac{\beta_e}{2}\right)$ is the sufficient condition for this case. Deriving the revenue function for the other three price regimes is straightforward so it is omitted to simplify the presentation.

E. AP-SP NEGOTIATION

In the negotiation stage, the AP decides if the AFD program is profitable to itself and if yes, which data unit price should be offered to the SP for its revenue loss. Hence, one can define the strategy pair (γ^{AP}, p^{AP}) for the AP in which $\gamma^{AP} \in \{0, 1\}$ represents the AFD participation of AP and $p^{AP} \in \Re^+$ is the data unit price as the base for payment to the SP. As we discussed in the previous section, a Category 1 application is offered free of charge to the users and the central part of the AP's revenue comes from advertisements. The advertisements price is related to the number of clicks, and it is accepted in related studies to connect the click frequency to the number of data requests from users. While it is common to consider a logarithmic payoff function for AP (e.g., see [29]), we aim to consider a worst-case scenario in which the revenue of AP is linearly related to the data requests. The benefit of such consideration is that by proving the possibility of AFD program under a linear revenue model of AP, the logarithmic revenue model also holds valid. The reason for the validity is the direction of payment which is from the AP to the SP. Thus, the more revenue AP makes, the bigger chance of using the AFD program. Since the type of revenue for the AP and SP is defined based on actually gained money by the AP, their utility is transferable by a side-payment. We define the revenue function of AP as follows:

$$\pi^{AP}(\gamma^{AP} = 0) = N\eta \int_{\alpha_e=0}^{1} d_e(\alpha_e, p) \, d\alpha_e, \quad (23)$$

$$\pi^{AP}(\gamma^{AP} = 1, p^{AP}) = ND_e\left(\eta - p^{AP}\right), \quad (24)$$

where η is the AP's revenue ratio for the overall usage of application type e. When $\gamma^{AP} = 0$, the AP does not make a side-payment to the SP and hence $p^{AP} = 0$. The overall data usage for $\gamma^{AP} = 1$ is ND_e which is considered together with a side-payment to the SP in (24). To make the cooperation feasible, the AP's revenue after cooperation should be greater than the sum of its revenue before implementing the AFD

program and the revenue loss of SP, that is:

$$ND_e\eta > N(\eta + p^o)\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) \, d\alpha_e \rightarrow$$

$$\eta > \frac{p^o \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) \, d\alpha_e}{D_e - \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) \, d\alpha_e}, \quad (25)$$

where p^o is the optimal price of SP in Stage I and $\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) \, d\alpha_e$ is the overall usage of application e in the non-cooperative form of the game. If the above feasibility condition holds, the AP can consider the AFD program. Otherwise, the best response of AP is $\gamma^{AP} = 0$. In the case of possible cooperation, the only remaining decision value for the AP is p^{AP} or in general, the amount of side-payment to the SP. Several options can be considered in such a case. One can find this game as a bargaining game and compute p^{AP} as the solution of a Nash bargaining game [32]. Another option is considering the game as a cooperative type. In this case, the solution concepts such as Core and Shapley value [33] can be applied. In this paper, we consider both the bargaining solution and the Shapley value.

F. NASH BARGAINING SOLUTION (NBS)

In this part, we find p^{AP} as a solution to the Nash bargaining game (NBS). Nash firstly introduced the NBS in [34] and described a bargaining situation in which players try to reach an agreement. The agreement can be a price definition or a contract between bargainers. Nash built his solution based on four axioms. Namely, Invariance to Equivalent Utility Representations, Symmetry, Independence of Irrelevant Alternatives, and Pareto efficiency. We refer the reader to [32] for more information on these axioms. In what follows we give a general definition of two-player NBS.

Definition 1: Consider two players 1 and 2 who try to reach an agreement in a bargaining game. Set A contains the agreement alternatives. If they cannot reach the agreement, a disagreement event D occurs. Players have a preference ordering on set $A \cup D$. We define $U^i : A \cup D \rightarrow \Re$ as the utility of player i. The union of all payoff pairs $(U^1(a), U^2(a))$ $a \in A$ is indicated by S. The disagreement utility point is defined by the pair $d = (U^1(D), U^2(D))$.

Definition 2 ([32]): The unique solution to Nash's four axioms of bargaining in a two player game is a pair $f^2 \in \Re^2$ given by:

$$f^2(S, d) = \underset{(d_1, d_2) < (s_1, s_2) \in S}{\arg\max} (s_1 - d_1)(s_2 - d_2). \quad (26)$$

If player 1 has a relative bargaining power $\zeta \in [0, 1]$ over its opponent, NBS is given by:

$$f^2(S, d) = \underset{(d_1, d_2) < (s_1, s_2) \in S}{\arg\max} (s_1 - d_1)^\zeta (s_2 - d_2)^{1-\zeta}. \quad (27)$$

Based on the above definition, we can define the following solution for our problem:

Proposition 4: In an AP-SP game in which the SP has a bargaining power $\zeta \in [0, 1]$ over AP, if $\zeta \geq$

$\dfrac{p^o(D_e - \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e)}{\eta D_e - (\eta + p^o)\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e}$ *and feasibility condition in (25) is satisfied, then the NBS price p_b^{AP} is given by:*

$$p_b^{AP} = \zeta\eta - \frac{(\zeta(\eta+p^o)-p^o)\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e}{D_e}, \quad (28)$$

otherwise, a disagreement occurs.

Nonnegative NBS price in (28) is supported by the AFD feasibility condition in (25). In other words, the NBS price (28) is not a solution for the AFD program if the feasibility condition of (25) does not hold. NBS price p^{AP} should be calculated for each pricing regime of the SP and its associated overall usage of application e. In Stage I of the game, since we already derived a closed-form representation of the parameters mentioned above under each pricing regime in Stage I of the game, we omit redundant equations that are created by straightforward parameter substitution.

G. SHAPLEY VALUE

The multi-stage game is considered as a strategic type and should be solved by the related solution concepts as we did in the previous subsection. However, in the game that we consider, increasing the revenue of AP does not decrease the revenue of SP. To be more precise, the AP and SP are not direct competitors. Thus, one can consider the AP-SP game as a cooperative form. There are several options to solve a coalitional game. As an option, we consider Shapley value which defines the revenue of each player by its relative power in the market. As previously mentioned, we know that the direction of payment is from AP to SP. Also, the utility of providers is represented by a monetary unit that is transferable. For such a case, the definition of Shapley value is as follows:

Definition 3: Consider an n-player game which the set of players N. The function $v(S)$ defines the utility of coalition $S \subset N$. The Shapley value to player $i \in N$ is defined by a unique function Φ that satisfies Shapley's three main axioms. Namely, Symmetry, Carrier and Linearity (see [35]) and is given by:

$$\Phi^i = \sum_{S \subseteq N\setminus\{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}\left(v(S \cup i) - v(S)\right). \quad (29)$$

For a two person game, the above equation gives:

$$\Phi^1 = \frac{1}{2}\left(v(12) + v(1) - v(2)\right), \quad (30)$$

$$\Phi^2 = \frac{1}{2}\left(v(12) + v(2) - v(1)\right), \quad (31)$$

where $v(12)$ is the revenue of cooperation.

Proposition 5: In the AP-SP game, the Shapley value of SP, Φ^{SP}, is given by $D_e \times p_{b|\zeta=\frac{1}{2}}^{AP}$, where $p_{b|\zeta=\frac{1}{2}}^{AP}$ is the NBS price with $\zeta = \frac{1}{2}$. Hence,

$$\Phi^{SP} = \frac{N}{2}\left(\eta D_e - (p^o+\eta)\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e\right). \quad (32)$$

For the proof, see Appendix D. In the next section, we show the feasibility of AFD program and the value of shared revenue for several numerical scenarios.
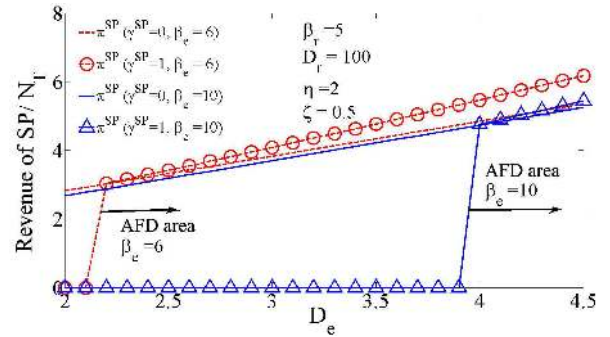

FIGURE 11. Revenue of SP with and without AFD program for different values of D_e and β_e.
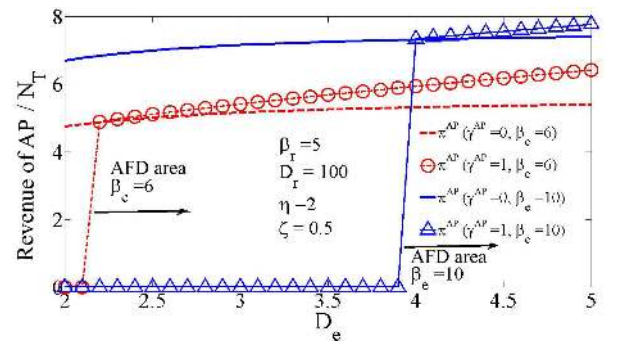

FIGURE 12. Revenue of AP with and without AFD program for different values of D_e and β_e.

V. NUMERICAL RESULTS

To have a visual representation of the AFD program feasibility, we consider several examples that differ in user and provider parameters such as D_e, β_e, η and bargaining power ζ. Similar to real markets and characteristics of type e and r applications, we set $\beta_e > \beta_r$, $D_r \gg 10\, D_e$, $D_r = 100$, and $\beta_r = 5$. These settings provide that the numerical examples follow the real behavior of cellular users covered in Ericsson's statistics. Our numerical analysis is focused on the revenue values of SP and AP, side-payment price p^{AP}, and the minimum required bargaining power of SP, ζ, that makes the AFD program feasible. We use D_e (the maximum desired usage of the eligible application) as the primary independent variable in the x-axis. However, in each example, there is an additional variable whose effect is shown by introducing several curves in each figure. For example, Figs. 11 and 12 represent the revenue of SP and AP, respectively, for $2 \leq D_e \leq 5$ and $\beta_e \in \{6, 10\}$. As indicated in Fig. 11, when the SP and AP have equal bargaining power, $\zeta = 0.5$, the desired AFD area starts from $D_e \cong 2.1$ when $\beta_e = 6$. Increasing β_e to 10, leads to slightly lower revenue for SP in Fig. 11 and notably higher revenue for AP in the non-AFD program in Fig. 12. The reason behind such behavior is that tye e applications generate a small portion of SP's revenue, while they are the main source of revenue for the AP. Hence, AP is not eager to make an AFD program when the maximum usage of type e application, D_e is not big enough. Since
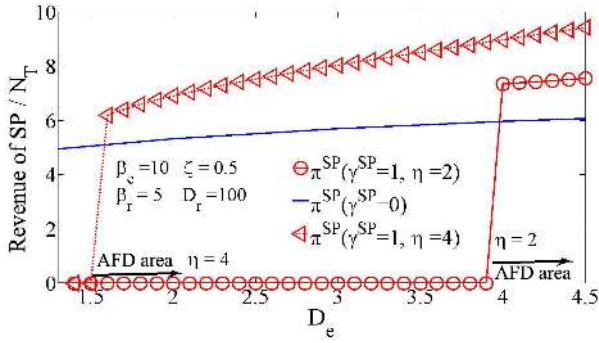
FIGURE 13. Revenue of SP with and without AFD program for different values of D_e and η.
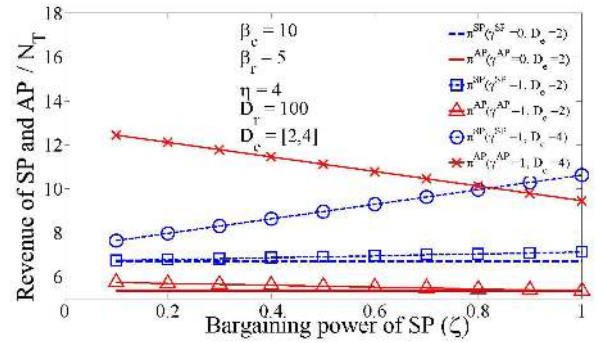

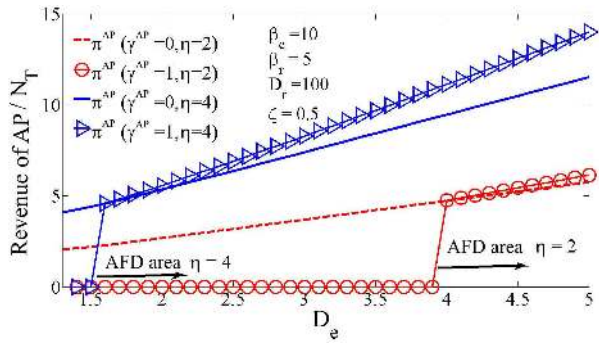**FIGURE 14.** Revenue of AP with and without AFD program for different values of D_e and η.
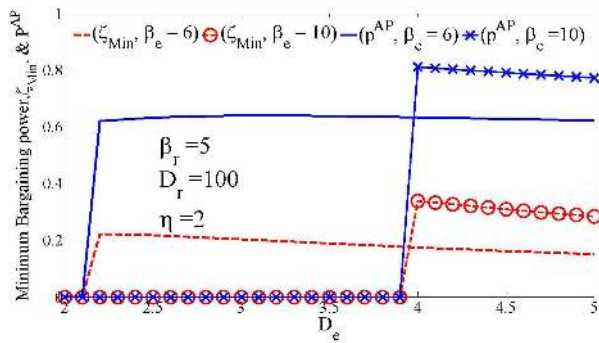

FIGURE 15. Minimum bargaining power, ζ, for AFD program and related p^{AP}.

with low values of D_e, the AFD program does not generate higher revenue for AP comparing to the non-AFD program. On the other hand, the bigger values of D_e such as $D_e > 3.9$ in Fig. 12 make the AFD program profitable since in that case, each user generates D_e units of traffic and bigger D_e means higher revenue for AP. In Figs. 13 and 14, β_e is fixed at 10 but the revenue factor of AP, η, is varied. As expected, increasing the value of η decreases the required value of D_e for AFD feasibility; since in case of having a bigger η, each unit of type e traffic generates higher revenue for the AP. In particular, for $\eta = 2$ the minimum value for D_e is 3.9 while for $\eta = 4$, D_e can be 1.5 or higher. Fig. 15 shows the unit price for side-payment, p^{AP}, and the minimum bargaining power,

FIGURE 16. Revenue of SP and AP with and without AFD program for different values of D_e and ζ.

ζ_{Min}, for the feasibility of AFD. For $\beta_e > \beta_r$, ζ_{Min} acquires a lower value comparing to $\beta_e = 10$. The main reason for this can be found in Fig. 11 where a lower β_e gives a higher revenue value to the SP while it is opposite for the AP's revenue given in Fig. 12. Hence, SP needs less bargaining power to dictate the AFD program. Finally, in Fig. 16 the bargaining power of SP, ζ, is set as the independent variable in the x-axis. Here we can observe two effects related to D_e and ζ. Firstly, by having a higher value of D_e, the overall revenues of both AP and SP increase. Secondly, by increasing ζ, the SP can force the AP to pay SP a bigger part of the AP revenue under the AFD program. Also, the bargaining power of 1 leaves no additional revenue for the AP in the AFD program. In summary, the presented results show the feasibility of the AFD program for the eligible applications, even if the AP revenue is linearly related to the size of transferred data.

VI. CONCLUSION
In this paper, we started by analyzing the recent statistics of user behavior in cellular markets and found three general types of applications in the mobile networks identified by their traffic pattern. Type-III applications such as Google Maps that require low bandwidth but carry sensitive information for the users are shown to be perfect candidates for the AFD program. This program should be implemented by cooperation between an SP and an AP. In the AFD program, the data usage associated with the eligible applications is free of charge. A mathematical framework for the feasibility of the AFD program is introduced. We built the framework by modeling the game as a Stackelberg game with two stages. In each stage, one group of market entities is involved; namely, users, an SP and an AP. The game is solved by backward induction. Finally, several numerical examples are constructed based on the user behavior data acquired from recent Internet statistics. Using these examples, we visually explained the conditions under which the AFD program is feasible. For future work, we aim to study the feasibility of AFD program for the applications with different business models such as health-care monitoring systems.

APPENDIXES

APPENDIX A
PROOF OF PROPOSITION 2

Comparing types e and r applications, if e belongs to Type-III group of applications, we have $\lim_{d\to 0} I^e(d) > I^r(d)$. For $d \to 0$ ($p < \max(\beta_e, \beta_r)$), the data usage for each application type i and user j is indicated by $\frac{\alpha_i^j \beta_i}{p} - 1$. With this condition, there are two group of users: the group of users with $\alpha_e \beta_e > \alpha_r \beta_r$ who prefer the application type e over r, and the group of users with $\alpha_e \beta_e < \alpha_r \beta_r$. As stated above, to have e as a Type-III application, when $d \to 0$, the overall usage of the first group should be greater than the second group, which means at near zero usage, the number of users in favor of application e should be greater than the other group, that is:

$$
\int_{\alpha_e=0}^{1} \int_{\alpha_r=0}^{\frac{\beta_e \alpha_e}{\beta_r}} f(\alpha_r) f(\alpha_e) d\alpha_r d\alpha_e
$$
$$
> \int_{\alpha_r=0}^{1} \int_{\alpha_e=0}^{\frac{\beta_r \alpha_r}{\beta_e}} f(\alpha_e) f(\alpha_r) d\alpha_e d\alpha_r
$$
$$
\to \frac{\beta_e}{\beta_r} > \frac{\beta_r}{\beta_e} \to \beta_e^2 > \beta_r^2, \tag{33}
$$

since both values are positive, the above inequality gives $\beta_e > \beta_r$. □

APPENDIX B
PROOF OF PROPOSITION 3

We must prove the concavity of the revenue function for $D_e \geq 1$. The revenue of SP in moderate price regime has a quadratic form with first and second derivatives as follows:

$$
\pi_m^{SP}(\gamma^{SP} = 0, p) = N\left(\frac{p^2}{2}\left(\frac{1}{\beta_r} - \frac{1}{\beta_e}((1 + D_e)^2 - 1)\right)\right.
$$
$$
\left. + (D_e - 1)p + \frac{\beta_r}{2}\right), \tag{34}
$$
$$
\frac{\partial \pi_m^{SP}(\gamma^{SP} = 0, p)}{\partial p} = N\left(p\left(\frac{1}{\beta_r} - \frac{1}{\beta_e}((1 + D_e)^2 - 1)\right)\right.
$$
$$
\left. + (D_e - 1)\right), \tag{35}
$$
$$
\frac{\partial^2 \pi_m^{SP}(\gamma^{SP} = 0, p)}{\partial p^2} = N\left(\left(\frac{1}{\beta_r} - \frac{1}{\beta_e}(D_e(D_e + 2))\right)\right). \tag{36}
$$

The first derivative has one extreme point at $p = \frac{\beta_e \beta_r (D_e - 1)}{\beta_r((1 + D_e)^2 - 1) - \beta_e}$. To have this point as a global maximum, we can prove that for $D_e \geq 1$, the extreme point is always positive and the second derivative in (36) is always negative:

$$
N\left(\left(\frac{1}{\beta_r} - \frac{1}{\beta_e}(D_e(D_e + 2))\right)\right) < 0 \to \beta_r > \frac{\beta_e}{D_e(D_e + 2)} \tag{37}
$$

which is always true, since the threshold order is $\beta_r > \frac{\beta_e}{D_e + 1}$. The above inequality also proves that the denominator of extreme point is always positive. Since $D_e \geq 1$, we have a positive extreme point with negative second derivative. Hence the extreme point is a global maximum for all $D_e \geq 1$, otherwise, for all $D_e < 1$ the extreme point is negative and the maximum of revenue function occurs at the lower limit of price $\frac{\beta_r}{D_r + 1}$. □

APPENDIX C
PROOF OF PROPOSITION 4

First we show the optimum value of p^{AP} and then prove the boundary value of ζ. By taking the equations $\pi^{SP}(\gamma^{SP} = 0)$ from (10), $\pi^{SP}(\gamma^{SP} = 1)$ from (11), $\pi^{AP}(\gamma^{AP} = 0)$ from (23), $\pi^{AP}(\gamma^{AP} = 0)$ from (24), and putting into the NBS objective function (27), we achieve (38), as shown at the bottom of this page. Based on the feasibility condition of (25) both parts of (38) are always positive. The first derivative of objective function in (39), as shown at the bottom of this page, has one extreme point in $p_b^{AP} = \zeta\eta - \frac{(\zeta(\eta + p^o) - p^o)\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) d\alpha_e}{D_e}$. The second derivative of objective function with respect to p^{AP} is given by (40), as shown at the bottom of this page, and is always negative. Hence the extreme point is a global maximum. For the lower and upper limits of ζ, we just check the given global maximum p_b^{AP} with $\epsilon_1(p_b^{AP}) > 0$ and $\epsilon_2(p_b^{AP}) > 0$ in (38). This gives us the boundary condition $\frac{p^o(D_e - \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) d\alpha_e)}{\eta D_e - (\eta + p^o)\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) d\alpha_e} \leq \zeta \leq 1$ for the relative bargaining power of SP. □

APPENDIX D
PROOF OF PROPOSITION 5

Considering the application type e, we have the total revenue of AFD program as $v(12) = v(SPAP) = \eta D_e$. Taking Shapely

---

$$
f(p^{AP}) = N^2 \left(\pi^{AP}(\gamma^{AP} = 1, p^{AP}) - \pi^{AP}(\gamma^{AP} = 0)\right)^\zeta \left(\pi^{SP}(\gamma^{SP} = 1, p^o) - \pi^{SP}(\gamma^{SP} = 0, p^o)\right)^{1-\zeta}
$$
$$
= N^2 \underbrace{\left(D_e(\eta - p^{AP}) - \eta \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) d\alpha_e\right)^\zeta}_{\epsilon_1(p^{AP})^\zeta} \underbrace{\left(D_e p^{AP} - p^o \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o) d\alpha_e\right)^{1-\zeta}}_{\epsilon_2(p^{AP})^{1-\zeta}}, \tag{38}
$$

$$
\frac{\partial f(p^{AP})}{\partial p^{AP}} = N^2 D_e \epsilon_1^\zeta \times \epsilon_2^{-\zeta} \times \left(-\zeta \epsilon_1^{-1} \epsilon_2 + 1 - \zeta\right), \tag{39}
$$

$$
\frac{\partial^2 f(p^{AP})}{\partial (p^{AP})^2} = -N^2 D_e^2 \zeta(1 - \zeta) \epsilon_1^\zeta \times \epsilon_2^{-\zeta} \times \left(\epsilon_1^{-2} \epsilon_2 + 2\epsilon_1^{-1} + \epsilon_2^{-1}\right). \tag{40}
$$

value of (30) and substituting the revenue of application type e from $\pi^{SP}(\gamma^{SP} = 0)$ (10) for $v(1)$ and $\pi^{AP}(\gamma^{AP} = 0)$ of (23) for $v(2)$, we have the following revenue share for AP and SP:

$$\Phi^{SP} = \frac{N}{2}\left(\eta \left(D_e + \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e \right) \right.$$
$$\left. -p^o \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e \right), \qquad (41)$$

$$\Phi^{AP} = \frac{N}{2}\left(\eta \left(D_e - \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e \right) \right.$$
$$\left. +p^o \int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e \right), \qquad (42)$$

since Φ^{SP} is defined as the side-payment from AP to SP, we can achieve p^{AP} as:

$$p^{AP} = \frac{\Phi^{SP}}{ND_e} \qquad (43)$$
$$= \frac{1}{2}\left(\eta + \frac{(\eta - p^o)\left(\int_{\alpha_e=0}^{1} d_e(\alpha_e, p^o)\, d\alpha_e \right)}{D_e} \right),$$

which is the NBS price in (28) with $\zeta = \frac{1}{2}$ ☐

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