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Research Article

Novel Data Sponsoring Control Scheme Based on the Dual-Leader Stackelberg Game Model

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In the phase of the process that will lead to the future 5G networks, the demand of mobile data usage will continue to rise sharply, and the high cost of data will become a critical concern. As a major paradigm shift, *data sponsoring* has been introduced with the hope of benefiting the practice of the telecommunication industry. The main idea of *data sponsoring* is to subsidize the service payment while appealing to more users; it can potentially generate more profit gains for both the users and the system operators. In this paper, the intelligent interactions of three network entities, i.e., the users, the service providers, and the content providers, are analyzed based on the basic ideas of game theory, and we design an effective *data sponsoring* control scheme using a novel dual-leader Stackelberg game model. As dual leaders, service and content providers share the profit in a cooperative manner, and mobile users react individually to the leaders in a competitive manner. By employing different game methodologies, we investigate the mutual relationship between the network entities and aim to balance the user's payoff and the system revenue. To validate the proposed approach, an analytic simulation model and numerical results are provided to demonstrate the efficiency and feasibility of the proposed approach under the 5G network infrastructure. Finally, we provide further challenges and various future opportunities in this research area.

1. Introduction

Currently, we are witnessing the explosive growth of global mobile data traffic, which reached 2.5 exabytes per month in 2014 and is predicted to exceed 24.3 exabytes per month by 2020. Furthermore, the total quantity of mobile devices worldwide will be 75 billion, while being more and more intelligent. According to Cisco, mobile video traffic will contribute to nearly 75% of the total mobile traffic. As more mobile users (MUs) watch more videos on their smart devices, video content providers (CPs), e.g., YouTube or Twitter, should be flexible in their management of the access to the data. The fast increase of mobile video traffic creates huge opportunities while also creating additional challenges for video CPs [1–4].

Usually, MUs are very sensitive to the service price while consuming video data. Therefore, one of most important challenges for the CPs is how to attract more MUs to access their data contents while achieving a higher revenue gain [5, 6]. In 2014, AT&T launched a new service paradigm called *data sponsoring*. The key idea of *data sponsoring* is to allow the CPs to subsidize the MU's price of video data consumption; it can attract more MUs and the benefit of the CPs is increased through selling more built-in advertisements. Clearly, *data sponsoring* potentially ensures a mutual advantage for the CPs and the MUs. As a real-world example, AT&T allows advertisers to sponsor video data to entice multiple MUs to watch advertisements they might otherwise have avoided [1, 7].

Between the CPs and the MUs, the service providers (SPs) act as liaison agents to provide data relay services such as network access and bandwidth provisioning. As a business entity, each SP also charges the MUs for service deliveries. The *data sponsoring* technique also has the potential to benefit the SPs. Usually, MUs are more attracted to lower service prices, occurring because of the CP's subsidies, and the SPs can enjoy additional revenues from the MUs' increased access demands [8]. Therefore, a remarkable interest from academia and the industry has emerged to investigate the interrelationship of the CPs, the SPs, and the MUs. This has led to research efforts to devise and innovate *data sponsoring* control protocols while creating a triple-win consequence for the three individual network entities. Usually, service-oriented architecture for *data sponsoring* consists of a policy and charging rules

function (PCRF), an online charging system, a deep packet inspection, a captive portal, an ad server, and a partner settlement module to suffice the end-to-end needs of an operator who launches the sponsored data plans [7, 8].

Traditional network management approaches are impractical for the special control issues related to *data sponsoring*, and we need a new control paradigm. Recently, game theory has been widely used in computer networks, from the problem of resource allocation to the competition analysis among network agents. In an environment consisting of mutually influential and intelligent network agents, game theory can provide a theoretical framework to discover the most advantageous choice. Games can be divided into noncooperative games and cooperative games. If rational decision makers can reach a binding agreement, then the game becomes a cooperative game. On the contrary, in a noncooperative game, this agreement cannot be reached. Today, game theory applies to a wide range of strategic selection problems, and it is now an umbrella term for the science of logical decision-making processes [9–11].

Recently, the Stackelberg game has been paid a lot of attention among different kinds of game models. In the traditional Stackelberg game, there are two different kinds of decision makers; a leader and multiple followers. A leader makes his decisions by considering the possible reactions of followers, and the followers react in a rational way to optimize their objective functions. Therefore, the Stackelberg game model is suitable for modeling a static bilevel optimization problem. In this study, we adopt the basic idea of the Stackelberg game model. However, to address the *data sponsoring* control problem, we extend the classical Stackelberg model; the CP and the SP are considered as dual game leaders, and multiple MUs are assumed as followers. They interact with each other dynamically to strike an appropriate system performance. So far, a few research papers dealing with the multileader Stackelberg game model have been presented. However, they have not properly justified the multileader coexistence problem.

Motivated by the above discussion, we propose a novel *data sponsoring* control scheme based on the dual-leader Stackelberg game model. As rational decision makers, the CP, the SP, and the MUs make control decisions in a systematic interactive feedback process. First, the leaders individually decide their service prices according to the iterative learning algorithm. Second, the followers react dynamically to maximize their payoffs. These two-step decision mechanisms are developed based on the noncooperative game approach. Because of the followers' decisions, the profit for the CP and the SP is secured. Based on the cooperative game approach, the profit can be shared between the CP and the SP in a fair-efficient manner. Using the Rubinstein bargaining model, the leaders pursue their mutual advantages in both competitive and cooperative manners.

1.1. Service-Oriented Architecture of Data Sponsoring. In a typical sponsored data scenario, users can browse websites, stream videos, and enjoy applications on their mobile devices without affecting their personal data plans. In return, subscribers watch advertisements, which are paid for by the advertising vendors directly to operators. This business model meets the needs of the advertisers/promoters, the content service operators, and the users. A sponsored data solution consists of a PCRF, an online charging System, a deep packet inspection, a captive portal, an ad server, and a partner settlement module to suffice the end-to-end needs of an operator who launches the sponsored data plans [12].

(i) *Communications service provider (CDR) reconciliation.* Sponsored data generates event CDRs, which can be processed by a technology platform. The CDRs contain information about the number of views/clicks for each advertisement. This information helps in generating the bill for an advertisement partner.

(ii) *Integrated policy and charging.* An online charging system, integrated with a 3GPP compliant PCRF enables SPs to offer new IP/IMS-based prepaid plans. It enables QoS for a partner service and facilitates partner pricing and charging, revenue sharing, revenue reconciliation, and settlement. It offers personalized plans and services to subscribers using policy analytics.

(iii) *Multiple networks.* A sponsored data solution can be used by various networks such as LTE, 3G, Wi-Fi, and fixed line

(iv) *Integration with existing systems.* Components of the solution can easily be integrated with the operators' existing 3rd party system.

(v) *Location-based services.* Owing to the solution, operators can have the benefit of location specific services such as location-based partnerships, location-specific promotions, and real-time location specific offerings

1.2. Related Work. Recently, *data sponsoring* has attracted more attention because of the improvement in the mutual benefits of the heterogeneous users, the CP, and the SP. In recent years, some papers have been published from the perspective of key techniques and challenges about the *data sponsoring* operations. The *sponsoring mobile data control* (*SMDC*) scheme formulates an analytical model to investigate the interactions of the CP, the SP, and the users while deriving their optimal behaviors [8]. First, the SP chooses the prices to charge the users and the CP. Second, the CP decides how much data to sponsor. Finally, the users choose how much data to consume from the CP by considering the sponsor amount and the SP's price. The CP, the SP, and the users attempt to maximize their payoffs individually, subject to the others' decisions. This sequential decision process is operated by the backward induction technique to find the efficient system outcome. Through numerical simulations, the *SMDC* scheme shows that data sponsorship disproportionately benefits the less cost-sensitive CP and the more cost-sensitive users [8].

The *cooperative data sponsor control* (*CDSC*) scheme [7] models the interactions of the users, the CP, and the SP as a two-stage Stackelberg game, where the SP and the CP act as the leaders determining the pricing and sponsoring strategies,

and the users act as the followers while deciding their data demands. As leaders, the SP and the CP make decisions and try to jointly optimize their strategies, with the purpose of maximizing their aggregate profits. In addition, the *CDSC* scheme exploits the local network effects by utilizing the structural properties of the underlying social networks, which improve the data demand largely. According to extensive simulations, it is shown that the payoffs of the users, the CP, and the SP are significantly improved, and it is revealed that the cooperation between the two leaders is the best choice for the users, the CP, and the SP [7].

The *hierarchical game-based data sponsoring* (*HGDS*) scheme models the interactions among the users, the CP, and the SP as a two-level hierarchical game [13]. In the developed game, the user-level subgame is designed as an evolutionary game, and the provider-level subgame is designed as a noncooperative game. To find the equilibrium, the *HGDS* scheme is developed based on the distributed and iterative approach. In addition, the market is featured by the global network effect in the perceived utility of a large population of users. Most of all, this study emphasizes two key issues: (i) the investigation of the evolution of the strategy of the user population, and (ii) the dynamics of the CP and the SP sponsoring in the model of a hierarchical market. Finally, both theoretical analysis and numerical simulation results have shown the effectiveness of the *HGDS* scheme [13]. In this paper, we compare our proposed scheme with the existing *SMDC* [8], *CDSC* [7], and *HGDS* [13] schemes and demonstrate that the proposed protocol based on the dual-leader Stackelberg game can significantly outperform these existing schemes.

1.3. Contribution. In this study, a novel *data sponsoring* control scheme is introduced by adopting the smart data pricing method. Based on the two different game methodologies, a mutually desirable solution can be achieved. To effectively operate the *data sponsoring*, we focus on the cooperation between the leaders and the competition between the leaders and the followers. The contributions of this paper can be summarized as follows:

(i) *Service price adjustment algorithm using online learning method.* We develop a new price adjustment algorithm for the leaders. Based on the iterative firefly learning mechanism, the price of the content and the service is adaptively adjusted in each time interval.

(ii) *Profit-sharing algorithm between CP and SP.* We develop a novel profit-sharing algorithm for the leaders. According to the concept of the Rubinstein bargaining model, both leaders can reach a fair-efficient agreement to split the profit.

(iii) *The synergy of competitive and cooperative game combination.* We explore the sequential interactions of price adjustment, the MUs' reactions, and profit-sharing processes and jointly design an integrated dual-leader Stackelberg game model to achieve mutual advantages. The synergy effect lies in the reciprocal combination of different game methodologies.

(iv) *Implementation practicality.* We consider an incomplete information environment to implement our *data sponsoring* control scheme. Although several schemes have been proposed to solve the same problem, they have concentrated on the ideal scenario with the complete system information, which does not occur in reality.

1.4. Organization. The remainder of this paper is structured as follows. In Section 2, the network system infrastructure to implement the *data sponsoring* technique is briefly explained. Subsequently, the price adjustment and profit-sharing algorithms for both leaders are designed, and the MU's decision procedure is simply given. Based on the dual-leader Stackelberg game model, the proposed *data sponsoring* scheme is described in detail while presenting the main algorithm steps. Section 3 presents the simulation results and discusses the performance compared to the existing *SMDC* [8], *CDSC* [7], and *HGDS* [13] protocols. Finally, our conclusions are summarized in Section 4. In addition, the topics of future research work are included in this section along with possible solutions.

2. The Proposed Data Sponsoring Control Scheme

In this section, we consider the *data sponsoring* system infrastructure consisting of three network entities: the CP, the SPs, and the MUs. Their interactions are modeled as a dual-leader Stackelberg game under an incomplete information environment. To achieve a mutually desirable solution, the game players dynamically interact with each other while adjusting their strategies.

2.1. Dual-Leader Stackelberg Game Model for CPs, SPs, and MUs. In this study, we assume that multimedia data consist of real content and advertisements and that the CP can subsidize the MUs' price of consuming multimedia data. The SP chooses the price to charge the MUs for data transmissions. Based on this *data sponsoring* scenario, we develop a new dual-leader Stackelberg game model where the CP, the SP, and the MUs are game players. As dual leaders, the CP and the SP select their price strategies based on the interactions of the MUs. As followers, the MUs decide whether to consume data. Each game player attempts to maximize their own payoff subject to other players' decisions. We formulate our dual-leader Stackelberg game as a three-stage sequential decision process: (i) the CP and the SP individually decide their price policies based on the online learning mechanism, (ii) the MUs react to the leaders' decisions in a noncooperative manner, and (iii) according to the Rubinstein bargaining solution, the CP and the SP share the profit, which comes from the MUs' payments. These processes are dynamically repeated until the best solution is obtained. Formally, we define our dual-leader Stackelberg game model $\mathbb{G} = \left\{\mathbb{N} = \left\{\{\mathrm{CP}, \mathrm{SP}_{1\le i\le n}\}, \left\{\mathrm{MU}^{\mathrm{SP}_i}_{1\le j\le m}\right\}\right\}, \mathbb{S} = \left\{\mathbb{S}^{\mathrm{CP}}, \mathbb{S}^{\mathrm{SP}}, \mathbb{S}^{\mathrm{MU}}\right\}, \mathbb{L} = \left\{\mathbb{L}^{\mathrm{CP}}, \mathbb{L}^{\mathrm{SP}}\right\}, \mathbb{U} = \left\{\mathbb{U}^{\mathrm{CP}}, \mathbb{U}^{\mathrm{SP}}, \mathbb{U}^{\mathrm{MU}}\right\}, \eta, T\right\}$ at each time period of the gameplay. Table 1 lists the notations used in this paper.

Table 1: Parameters used in the proposed algorithm.

Notations	Explanation
CP	Content provider
MU	Mobile user
SP	Service provider
$\mathbb{S}^{\mathrm{CP}} = \{\mathfrak{B}^{\mathrm{CP}}_{\min} \cdots \mathfrak{B}^{\mathrm{CP}}_{w} \cdots \mathfrak{B}^{\mathrm{CP}}_{\max}\}$	The strategy set of CP
$\mathfrak{B}^{\mathrm{CP}}_{w}$	The w^{th} *data sponsoring* level for MUs
$\mathbb{S}^{\mathrm{SP}} = \{\mathfrak{Z}^{\mathrm{SP}}_{\min} \cdots \mathfrak{Z}^{\mathrm{SP}}_{k} \cdots \mathfrak{Z}^{\mathrm{SP}}_{\max}\}$	The strategy set of SP
$\mathfrak{Z}^{\mathrm{SP}}_{k}$	The kth price level for MUs
$\mathbb{S}^{\mathrm{MU}} = \{\mathrm{on}, \mathrm{off}\}$	The strategy set of MUs
$\mathbb{L}^{\mathrm{CP}} = [\psi^{\mathfrak{B}^{\mathrm{CP}}_{\min}} \cdots \psi^{\mathfrak{B}^{\mathrm{CP}}_{w}} \cdots \psi^{\mathfrak{B}^{\mathrm{CP}}_{\max}}]$	The CP's leaning vector
$\psi^{\mathfrak{B}^{\mathrm{CP}}_{w}}$	The strategy $\mathfrak{B}^{\mathrm{CP}}_{w}$'s propensity
$\mathbb{L}^{\mathrm{SP}} = [\xi^{\mathfrak{Z}^{\mathrm{SP}}_{\min}} \cdots \xi^{\mathfrak{Z}^{\mathrm{SP}}_{k}} \cdots \xi^{\mathfrak{Z}^{\mathrm{SP}}_{\max}}]$	The SP's leaning vector
$\xi^{\mathfrak{Z}^{\mathrm{SP}}_{k}}$	The strategy $\mathfrak{Z}^{\mathrm{SP}}_{k}$'s propensity
$\mathbb{U}^{\mathrm{CP}}$, $\mathbb{U}^{\mathrm{SP}}$, $\mathbb{U}^{\mathrm{MU}}$	The payoffs of CP, SP and MU, respectively
η	The CP's fixed unit price per bit
N^{SP_i}	The set of MUs, who actively consume the data through the SP_i
$\mathcal{S}_{\mathfrak{H}_t}(\cdot)$	The function to share the profit between CP and SP at time $\mathfrak{H}_t$
$\mathcal{C}^{\mathrm{CP}}_{\mathfrak{H}_t}(N^{\mathrm{SP}_i})$	The CP's cost function
$\mathcal{C}^{\mathrm{SP}_i}_{\mathfrak{H}_t}(N^{\mathrm{SP}_i})$	The SP's cost function
$\mathcal{F}^{\mathrm{data}}_{\mathfrak{H}_t}(N^{\mathrm{SP}_i}, \mathfrak{H}_t)$	The function to summarize the total consuming data
r^{SP}_{c}	A cost factor of the SP
$\Theta^{\mathrm{CP}}_{\mathfrak{H}_t}(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i})$	The *data sponsoring* subsidy by the CP's strategy $\mathfrak{B}^{\mathrm{CP}}_{w}$
$\mathcal{V}^{\mathrm{CP}}_{\mathfrak{H}_t}(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i})$	The extra revenue function
$\mathcal{R}^{\mathrm{CP}}$	The revenue rate per data consuming amount
β^{CP}	The attractiveness between ψ's
γ	A coefficient to control the convergence rate
α^{CP}	A regulating parameter
$\mathbf{P}^{\mathfrak{B}^{\mathrm{CP}}}_{\mathfrak{H}} = [P^{\mathfrak{B}^{\mathrm{CP}}_{\min}}_{\mathfrak{H}} \cdots P^{\mathfrak{B}^{\mathrm{CP}}_{\max}}_{\mathfrak{H}}]$	The CP's probability distribution
$\mathbf{P}^{\mathfrak{Z}^{\mathrm{SP}}}_{\mathfrak{H}} = [P^{\mathfrak{Z}^{\mathrm{SP}}_{\min}}_{\mathfrak{H}} \cdots P^{\mathfrak{Z}^{\mathrm{SP}}_{\max}}_{\mathfrak{H}}]$	The SP's probability distribution
χ_{MU_j}	The data consuming amount of the MU_j
$\mathfrak{A}(\cdot)$	The MU_j's satisfaction function
$\mathfrak{C}(\cdot)$	The MU_j's cost function
$\phi^{\mathrm{MU}_j}_{\mathfrak{H}_t} = \{0, 1\}$	The MU's strategy for data consumption
δ_{CP}, δ_{SP}	The bargaining powers of the CP and SP
x^*_{CP}, x^*_{SP}	The profit division ratio of CP and SP
Δ	The fixed time period of negotiation round
$\mathcal{J}$	A weight factor to adjust the bargaining power

(i) $\mathbb{N}$ is the finite set of game players. We model a monopoly CP scenario to analyze the impact of *data sponsoring* on multiple SPs and MUs; there are n SPs and m MUs where $\mathrm{MU}^{\mathrm{SP}_i}_{1 \le j \le m}$ represents the jth MU in the covering area of SP_i.

(ii) $\mathbb{S}$ is the finite set of each player's strategies, which are defined discretely. $\mathbb{S}^{\mathrm{CP}} = \{\mathfrak{B}^{\mathrm{CP}}_{\min} \cdots \mathfrak{B}^{\mathrm{CP}}_{w} \cdots \mathfrak{B}^{\mathrm{CP}}_{\max}\}$ is the strategy set of the CP where $\mathfrak{B}^{\mathrm{CP}}_{w}$ represents the w^{th} *data sponsoring* level for the MUs. $\mathbb{S}^{\mathrm{SP}} = \{\mathfrak{Z}^{\mathrm{SP}}_{\min} \cdots \mathfrak{Z}^{\mathrm{SP}}_{k} \cdots \mathfrak{Z}^{\mathrm{SP}}_{\max}\}$ is the strategy set of the SP where $\mathfrak{Z}^{\mathrm{SP}}_{k}$ represents the kth price level for the MUs. $\mathbb{S}^{\mathrm{MU}} = \{\mathrm{on}, \mathrm{off}\}$ is the strategy set of the MUs where on, off represent whether the MUs are consuming data or not.

(iii) $\mathbb{U}$ is the utility set of each player's payoffs where $\mathbb{U}^{\mathrm{CP}}$, $\mathbb{U}^{\mathrm{SP}}$, and $\mathbb{U}^{\mathrm{MU}}$ represent the payoffs of the CP, the SP, and the MU, respectively.

(iv) $\mathbb{L}$ is the finite set of leaning vectors. $\mathbb{L}^{\mathrm{CP}} = [\psi^{\mathfrak{B}^{\mathrm{CP}}_{\min}} \cdots \psi^{\mathfrak{B}^{\mathrm{CP}}_{w}} \cdots \psi^{\mathfrak{B}^{\mathrm{CP}}_{\max}}]$ is the CP's leaning vector where $\psi^{\mathfrak{B}^{\mathrm{CP}}_{w}}$ represents the strategy $\mathfrak{B}^{\mathrm{CP}}_{w}$'s propensity. $\mathbb{L}^{\mathrm{SP}} = [\xi^{\mathfrak{Z}^{\mathrm{SP}}_{\min}} \cdots \xi^{\mathfrak{Z}^{\mathrm{SP}}_{k}} \cdots \xi^{\mathfrak{Z}^{\mathrm{SP}}_{\max}}]$ is the SP's leaning vector where $\xi^{\mathfrak{Z}^{\mathrm{SP}}_{k}}$ represents the strategy $\mathfrak{Z}^{\mathrm{SP}}_{k}$'s propensity; in the next time period, $\mathbb{L}$ is used to estimate the strategy selection probability for the CP and the SP's strategy decisions.

(v) η is the CP's fixed unit price per bit for the provision of the data content.

(vi) $T = \{\mathfrak{H}_1, \ldots, \mathfrak{H}_t, \mathfrak{H}_{t+1}, \ldots\}$ denotes time, which is represented by a sequence of time steps with imperfect information for the dual-leader Stackelberg game process.

The first process in our dual-leader Stackelberg game is the leader's price decision algorithm. From the viewpoint of the CP and the SP, they select their strategies in the $\mathbb{S}^{\mathrm{CP}}$ and the $\mathbb{S}^{\mathrm{SP}}$ to maximize their payoffs. Simply, the utility functions of the CP and the SP_i ($\mathbb{U}^{\mathrm{CP}}_{\mathfrak{H}_t}$ and $\mathbb{U}^{\mathrm{SP}_i}_{\mathfrak{H}_t}$) at time $\mathfrak{H}_t$ are be defined as follows:

$$\begin{cases} \mathbb{U}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}\right) = \Big(\mathcal{S}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i}\right) \\ \qquad - \left(\mathcal{C}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}\right) + \Theta^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i}\right)\right) \\ \qquad + \mathcal{V}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i}\right)\Big), \\ \mathbb{U}^{\mathrm{SP}_i}_{\mathfrak{H}_t}\left(\mathfrak{Z}^{\mathrm{SP}_i}_{k}\right) = \left(\mathcal{S}^{\mathrm{SP}}_{\mathfrak{H}_t}\left(\mathfrak{Z}^{\mathrm{SP}_i}_{k}, N^{\mathrm{SP}_i}\right) - \mathcal{C}^{\mathrm{SP}_i}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}\right)\right), \end{cases}$$

$$\text{s.t.} \begin{cases} \mathcal{C}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}\right) = \mathcal{F}^{\mathrm{data}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}, \mathfrak{H}_t\right) \times \eta, \\ \Theta^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i}\right) = \left(\mathcal{F}^{\mathrm{data}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}, \mathfrak{H}_t\right) \times \eta\right) \times \mathfrak{B}^{\mathrm{CP}}_{w}, \\ \mathcal{V}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i}\right) = \mathcal{F}^{\mathrm{data}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}, \mathfrak{H}_t\right) \times \mathcal{R}^{\mathrm{CP}}, \\ \mathcal{C}^{\mathrm{SP}_i}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}\right) = \mathcal{F}^{\mathrm{data}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}_i}, \mathfrak{H}_t\right) \times r^{\mathrm{SP}}_{c}, \end{cases} \tag{1}$$

where N^{SP_i} is the set of MUs who actively consume the data through the SP_i. $\mathcal{S}_{\mathfrak{H}_t}(\cdot)$ is a function that represents the profit sharing between the CP and the SP at time $\mathfrak{H}_t$; it is defined in the leader's profit-sharing algorithm based on the Rubinstein bargaining approach. $\mathcal{C}^{\mathrm{CP}}_{\mathfrak{H}_t}(N^{\mathrm{SP}_i})$ and $\mathcal{C}^{\mathrm{SP}_i}_{\mathfrak{H}_t}(N^{\mathrm{SP}_i})$ are the CP and the SP's cost functions to provide data services for the MUs in N^{SP_i}, respectively. $\mathcal{F}^{\mathrm{data}}_{\mathfrak{H}_t}(N^{\mathrm{SP}_i}, \mathfrak{H}_t)$ is a function that represents the total amount of data consumed from the N^{SP_i} at time $\mathfrak{H}_t$. r^{SP}_{c} is a cost factor for the data service of the SP. $\Theta^{\mathrm{CP}}_{\mathfrak{H}_t}(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}_i})$ is the *data sponsoring*

subsidy by the CP's strategy $\mathfrak{B}_w^{\mathrm{CP}}$ for the MUs in N^{SP_i}. $\mathscr{V}_{\mathfrak{H}_t}^{\mathrm{CP}}(\mathfrak{B}_w^{\mathrm{CP}}, N^{\mathrm{SP}_i})$ is the extra revenue function from the advertisement selling, and $\mathscr{R}^{\mathrm{CP}}$ is the revenue rate per amount of data consumed.

As game leaders, the main goal of the CP and the SP is to maximize their utility functions by rationally selecting their strategies, i.e., $\mathfrak{B}^{\mathrm{CP}}$ and $\mathfrak{Z}^{\mathrm{SP}}$. In the situation where information is incomplete, it is necessary for the CP and the SP to learn the condition of the current system while self-adapting their actions to respond quickly to real-time network dynamics. Therefore, the CP and the SP should adopt a learning technique to decide their next strategies by using their accumulated knowledge. So far, several learning methods have been developed to help game players who have incomplete information about their dynamic network environments.

In 2008, Fister et al. proposed a novel swarm intelligence method, called the firefly mechanism, which was inspired by the flashing lights of fireflies in nature. It is a kind of stochastic, nature-inspired, metaheuristic algorithm that can be applied for solving the hardest optimization problems. In the firefly mechanism, a solution is discovered by trial and error [14]. In this study, we adopt the basic idea of the firefly mechanism to design our CP and SP's strategy decision algorithm. At time $\mathfrak{H}_{t-1}$, the strategy $\mathfrak{B}_w^{\mathrm{CP}}$ in $\mathbb{S}^{\mathrm{CP}}$ is selected by the CP; the selection propensity of $\mathfrak{B}^{\mathrm{CP}}$ for the time $\mathfrak{H}_t$ ($\psi_{\mathfrak{H}_t}^{\mathfrak{B}^{\mathrm{CP}}}$) in $\mathbb{L}^{\mathrm{CP}}$ is modified as follows:

$$\begin{cases} \psi_{\mathfrak{H}_t}^{\mathfrak{B}_w^{\mathrm{CP}}} = \psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_w^{\mathrm{CP}}} + \left(\alpha^{\mathrm{CP}} \times \mathscr{R}\right) + \left(\dfrac{1}{\left\|\mathbb{S}^{\mathrm{CP}}\right\| - 1} \times \displaystyle\sum_{\mathfrak{B}_g^{\mathrm{CP}} \in \mathbb{S}^{\mathrm{CP}}, \mathfrak{B}_g^{\mathrm{CP}} \neq \mathfrak{B}_w^{\mathrm{CP}}} \left(\left[1 - \left(\beta^{\mathrm{CP}}\right)\right] \times \mathfrak{M}^{\mathrm{CP}}\right)\right), & \text{if } \mathfrak{B}_w^{\mathrm{CP}} \text{ is selected at time } \mathfrak{H}_{t-1}, \\ \psi_{\mathfrak{H}_t}^{\mathfrak{B}_f^{\mathrm{CP}}} = \psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_f^{\mathrm{CP}}}, & \text{if } \mathfrak{B}_f^{\mathrm{CP}} \neq \mathfrak{B}_w^{\mathrm{CP}}, \end{cases}$$

$$\text{s.t.} \quad \begin{cases} F\left(\psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_g^{\mathrm{CP}}}, \psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_w^{\mathrm{CP}}}\right) = \sqrt{\left(\psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_g^{\mathrm{CP}}} - \psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_w^{\mathrm{CP}}}\right)^2}, \\ \mathfrak{M}^{\mathrm{CP}} = \dfrac{\mathbb{U}_{\mathfrak{H}_{t-1}}^{\mathrm{CP}}\left(\mathfrak{B}_w^{\mathrm{CP}}\right) - \mathbb{U}_{\mathfrak{H}_{t-1}}^{\mathrm{CP}}\left(\mathfrak{B}_g^{\mathrm{CP}}\right)}{\mathbb{U}_{\mathfrak{H}_{t-1}}^{\mathrm{CP}}\left(\mathfrak{B}_w^{\mathrm{CP}}\right)}, \\ R = \left(\mathrm{rand}_0^1 - \varepsilon\right), \end{cases} \tag{2}$$

where β^{CP} is the attractiveness when the difference between $\psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_w^{\mathrm{CP}}}$ and $\psi_{\mathfrak{H}_{t-1}}^{\mathfrak{B}_g^{\mathrm{CP}}}$ is the highest. Therefore, the $\psi^{\mathfrak{B}_w^{\mathrm{CP}}}$ value is adjusted based on the strategy $\mathfrak{B}_w^{\mathrm{CP}}$'s relative preference to the strategy $\mathfrak{B}_g^{\mathrm{CP}}$ and γ is a coefficient, which controls the convergence rate. In addition, the randomized searching process is used to explore, with a regulating parameter α^{CP} and the function rand_0^1, which generates a random number within [0, 1]. According to $\psi_{\mathfrak{H}_t}^{\mathfrak{B}^{\mathrm{CP}}}$ values in $\mathbb{L}^{\mathrm{CP}}$, the $\mathfrak{B}_w^{\mathrm{CP}}$ strategy selection probability at time $\mathfrak{H}_t$ ($P_{\mathfrak{H}_t}^{\mathfrak{B}_w^{\mathrm{CP}}}$) is finally defined as follows:

$$P_{\mathfrak{H}_t}^{\mathfrak{B}_w^{\mathrm{CP}}} = \frac{\mathrm{EXP}\left(\psi_{\mathfrak{H}_t}^{\mathfrak{B}_w^{\mathrm{CP}}}\right)}{\sum_{\mathfrak{B}_g^{\mathrm{CP}} \in \mathbb{S}^{\mathrm{CP}}} \left(\mathrm{EXP}\left(\psi_{\mathfrak{H}_t}^{\mathfrak{B}_g^{\mathrm{CP}}}\right)\right)}. \tag{3}$$

At each time period, the CP dynamically selects their strategies based on the probability distribution $\mathbf{P}_{\mathfrak{H}}^{\mathfrak{B}^{\mathrm{CP}}} = [P_{\mathfrak{H}}^{\mathfrak{B}_{\min}^{\mathrm{CP}}} \cdots P_{\mathfrak{H}}^{\mathfrak{B}_{\max}^{\mathrm{CP}}}]$; this approach can make the CP more responsive to the current system conditions. With the CP, the SP also periodically modifies the selection propensity ($\xi^{\mathfrak{Z}^{\mathrm{SP}}}$) of strategy $\mathfrak{Z}^{\mathrm{SP}}$ in $\mathbb{S}^{\mathrm{SP}}$ and their selection probability $P_{\mathfrak{H}}^{\mathfrak{Z}^{\mathrm{SP}}}$ in the same manner as the CP does. In this study, a single CP carries out the dual-leader Stackelberg game with multiple SPs in parallel. Therefore, the CP's strategy is selected separately to the MUs, who access data contents through different SPs, and each SP also interacts with the CP independently to decide their strategy $\mathfrak{Z}^{\mathrm{SP}}$ based on the probability distribution $\mathbf{P}_{\mathfrak{H}}^{\mathfrak{Z}^{\mathrm{SP}}} = [P_{\mathfrak{H}}^{\mathfrak{Z}_{\min}^{\mathrm{SP}}} \cdots P_{\mathfrak{H}}^{\mathfrak{Z}_{\max}^{\mathrm{SP}}}]$.

The second process in our dual-leader Stackelberg game is the followers' reaction mechanism, which deals with the problem of maximizing the MU's utility function and decides the leaders' profit at time $\mathfrak{H}_t$ ($\mathfrak{X}_{\mathfrak{H}_t}^{\mathrm{CP,SP}}$). Traditionally, the MU's utility function is defined by considering the reciprocal relationship between the satisfaction and the paying

cost. As followers, the major goal of the jth MU (MU_j) is to decide their strategies to satisfy the following equation:

$$\max_{\phi_{\mathfrak{H}_t}^{\mathrm{MU}_j}\in\mathbb{S}^{\mathrm{MU}}} \mathbb{U}_{\mathfrak{H}_t}^{\mathrm{MU}_j}\left(\phi_{\mathfrak{H}_t}^{\mathrm{MU}_j},\chi_{\mathrm{MU}_j},\left(\mathfrak{B}_w^{\mathrm{CP}},\mathfrak{Z}_k^{\mathrm{SP}_i}\right)\right)=\max_{\phi_{\mathfrak{H}_t}^{\mathrm{MU}_j}\in\mathbb{S}^{\mathrm{MU}}}\left(\left[\mathfrak{A}\left(\chi_{\mathrm{MU}_j}\right)+\Theta_{\mathfrak{H}_t}^{\mathrm{CP}}\left(\mathfrak{B}_w^{\mathrm{CP}},\chi_{\mathrm{MU}_j}\right)-\mathfrak{C}\left(\left(\mathfrak{B}_w^{\mathrm{CP}},\mathfrak{Z}_k^{\mathrm{SP}_i}\right),\chi_{\mathrm{MU}_j}\right)\right]\times\phi_{\mathfrak{H}_t}^{\mathrm{MU}_j}\right),$$

$$\text{s.t.}\quad\begin{cases}\mathfrak{A}\left(\chi_{\mathrm{MU}_j}\right)=\left[\left(\vartheta\times\log\left(1+\dfrac{\chi_{\mathrm{MU}_j}}{\mathrm{Gbps}}\right)\right)\times\chi_{\mathrm{MU}_j}\right],\\[2ex]\mathfrak{C}\left(\left(\mathfrak{B}_w^{\mathrm{CP}},\mathfrak{Z}_k^{\mathrm{SP}_i}\right),\chi_{\mathrm{MU}_j}\right)=\left(\chi_{\mathrm{MU}_j}\times\left(\eta+\mathfrak{Z}_k^{\mathrm{SP}_i}\right)\right),\end{cases}\tag{4}$$

$$\phi_{\mathfrak{H}_t}^{\mathrm{MU}_j}=\begin{cases}1, & \text{if } \phi_{\mathfrak{H}_t}^{\mathrm{MU}_j} \text{ is on},\\ 0, & \text{if } \phi_{\mathfrak{H}_t}^{\mathrm{MU}_j} \text{ is off},\end{cases}$$

where χ_{MU_j} is the amount of data consumed by MU_j and SP_i is MU_j's connecting SP. $\mathfrak{A}(\cdot)$ and $\mathfrak{C}(\cdot)$ are MU_j's satisfaction and cost functions. In a noncooperative game manner, MU_j rationally selects their strategy $\phi_{\mathfrak{H}_t}^{\mathrm{MU}_j}$ to maximize the $\mathbb{U}_{\mathfrak{H}_t}^{\mathrm{MU}_j}(\cdot)$.

2.2. The Leaders' Profit-Sharing Algorithm. For cooperative games, bargaining solutions are well-known solutions, which provide predictions about how the profit will be fairly shared while making a joint agreement. Various bargaining solutions have been proposed based on slightly different assumptions about what properties are desired. To obtain unique predictions in bargaining games, Israeli economist Ariel Rubinstein built up an alternating-offer bargain solution, called the Rubinstein bargaining solution (RBS), by employing Selten's idea of a subgame-perfect equilibrium. It provides a solution to a class of bargaining games that feature alternating offers through an infinite time horizon. For a long time, a solution to this type of a bargaining game was a mystery. Therefore, Rubinstein's solution is one of the most influential findings in cooperative game theory, and it can provide a possible bargaining solution with the fair-efficient division of the players' profits [15–17]. In the proposed *data sponsoring* scheme, the profit-sharing problem between the CP and the SP is formulated according to the RBS concept. One intuitive message of the basic RBS model is that frictionless bargaining processes are indeterminate. If the players do not care about the time at which agreement is struck, then there is nothing to prevent them from haggling for as long as they wish. Conversely, frictions in the bargaining process may provide the players with some incentive to reach an agreement.

In the scenario of the RBS, two players are bargaining about the division of the profit while having their own bargaining powers (δ). Based on their bargaining power, the players negotiate with each other by proposing offers alternately. A player with more bargaining power benefits more from the bargaining. After several rounds of negotiation, an agreement between the CP and the SP ($\mathrm{RBS}(x_{\mathrm{CP}}^*,x_{\mathrm{SP}}^*)$) is given by [15–17]

$$\mathrm{RBS}\left(x_{\mathrm{CP}}^*,x_{\mathrm{SP}}^*\right)=\begin{cases}\left(\dfrac{1-\delta_{\mathrm{SP}}}{1-\left(\delta_{\mathrm{CP}}\times\delta_{\mathrm{SP}}\right)},\dfrac{\delta_{\mathrm{SP}}\times\left(1-\delta_{\mathrm{CP}}\right)}{1-\left(\delta_{\mathrm{CP}}\times\delta_{\mathrm{SP}}\right)}\right), & \text{if the player CP offers first},\\[2ex]\left(\dfrac{\delta_{\mathrm{CP}}\times\left(1-\delta_{\mathrm{SP}}\right)}{1-\left(\delta_{\mathrm{CP}}\times\delta_{\mathrm{SP}}\right)},\dfrac{1-\delta_{\mathrm{CP}}}{1-\left(\delta_{\mathrm{CP}}\times\delta_{\mathrm{SP}}\right)}\right), & \text{if the player SP offers first},\end{cases}\tag{5}$$

$$\text{s.t.}\quad\left(x_{\mathrm{CP}}^*,x_{\mathrm{SP}}^*\right)\in R^2\ :\ x_{\mathrm{CP}}^*+x_{\mathrm{SP}}^*=1,\quad x_{\mathrm{CP}}^*\geq 0,\ x_{\mathrm{SP}}^*\geq 0, 0\leq\delta_{\mathrm{CP}},\delta_{\mathrm{SP}}\leq 1,$$

where δ_{CP} and δ_{SP} are the bargaining powers of the CP and the SP, respectively. x_{CP}^* and x_{SP}^* are the profit division ratios of the CP and the SP, respectively. Therefore, the leaders' profit $\mathfrak{X}$, which is the sum of the data consuming MU's $\mathfrak{C}(\cdot)$, is divided by the rate of $x_{\mathrm{CP}}^*:x_{\mathrm{SP}}^*$. It means that the $\mathcal{S}_{\mathfrak{H}_t}^{\mathrm{CP}}(\mathfrak{B}^{\mathrm{CP}},N^{\mathrm{SP}})$ and $\mathcal{S}_{\mathfrak{H}_t}^{\mathrm{SP}}(\mathfrak{Z}^{\mathrm{SP}},N^{\mathrm{SP}})$ functions in equation (1) are defined as follows:

$$\begin{cases}\mathcal{S}_{\mathfrak{H}_t}^{\mathrm{CP}}\left(\mathfrak{B}^{\mathrm{CP}},N^{\mathrm{SP}}\right)=\mathfrak{X}_{\mathfrak{H}_t}^{\mathrm{CP,SP}}\times\dfrac{x_{\mathrm{CP}}^*}{\left(x_{\mathrm{CP}}^*+x_{\mathrm{SP}}^*\right)},\\[2ex]\mathcal{S}_{\mathfrak{H}_t}^{\mathrm{SP}}\left(\mathfrak{Z}^{\mathrm{SP}},N^{\mathrm{SP}}\right)=\mathfrak{X}_{\mathfrak{H}_t}^{\mathrm{CP,SP}}\times\dfrac{x_{\mathrm{SP}}^*}{\left(x_{\mathrm{CP}}^*+x_{\mathrm{SP}}^*\right)},\end{cases}\tag{6}$$

It is obvious that there is a first-proposer advantage in the bargaining process. In our dual-leader cooperation algorithm, the leader, who has a larger value of its cost function $\mathscr{C}(\cdot)$, becomes a first-proposer to compensate for its control overhead. Traditionally, the bargaining power in the Rubinstein–Stahl model is defined as follows:

$$\delta_{\mathrm{CP}} = \frac{\exp\left(\mathscr{J}_{\mathrm{CP}} \times \Delta\right)}{\exp\left(\mathscr{J}_{\mathrm{CP}} \times \Delta\right) + \exp\left(\mathscr{J}_{\mathrm{SP}} \times \Delta\right)},$$
$$\delta_{\mathrm{SP}} = \frac{\exp\left(\mathscr{J}_{\mathrm{SP}} \times \Delta\right)}{\exp\left(\mathscr{J}_{\mathrm{CP}} \times \Delta\right) + \exp\left(\mathscr{J}_{\mathrm{SP}} \times \Delta\right)}, \tag{7}$$

where Δ is the fixed time period of a negotiation round and $\mathscr{J}$ is a weight factor to adaptively adjust the bargaining power δ, which increases monotonically with $\mathscr{J}$. During the *data sponsoring* operations, each leader has a different weight factor. To provide more fair-efficient control over the collaboration between the CP and the SP, this factor value should be adjusted dynamically under various system situations. In our dual-leader profit-sharing algorithm, the leader's operating cost is used to set the value of $\mathscr{J}$. If one leader has a relatively higher cost to provide data services, we give preference to that leader with a higher value of the weight factor. At time $\mathfrak{H}_t$, the $\mathscr{J}_{\mathrm{CP}}$ and $\mathscr{J}_{\mathrm{SP}}$ values are given by

$$\begin{cases} \mathscr{J}_{\mathrm{CP}} = \dfrac{\left(\mathscr{C}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}}\right) + \Theta^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}}\right)\right)}{\left(\left(\mathscr{C}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}}\right) + \Theta^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}}\right)\right) + \mathscr{C}^{\mathrm{SP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}}\right)\right)}, \\ \mathscr{J}_{\mathrm{SP}} = \dfrac{\mathscr{C}^{\mathrm{SP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}}\right)}{\left(\left(\mathscr{C}^{\mathrm{CP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}}\right) + \Theta^{\mathrm{CP}}_{\mathfrak{H}_t}\left(\mathfrak{B}^{\mathrm{CP}}_{w}, N^{\mathrm{SP}}\right)\right) + \mathscr{C}^{\mathrm{SP}}_{\mathfrak{H}_t}\left(N^{\mathrm{SP}}\right)\right)}. \end{cases} \tag{8}$$

During the *data sponsoring* system operations, the discount factors of leaders, i.e., $\mathscr{J}_{\mathrm{CP}}$ and $\mathscr{J}_{\mathrm{SP}}$, are adaptively adjusted to find the best solution. Therefore, the obtained profit can be dynamically shared by the CP and the SP while adaptively responding to the current *data sponsoring* system conditions.

2.3. Main Steps of the Proposed Data Sponsoring Control Scheme. The explosive growth of mobile video traffic introduces challenges for the future 5G wireless networks. The *data sponsoring* technology has emerged as one of the key enablers to attract more MUs. In this paper, we study a joint design of competitive and cooperative interactions among the CP, the SPs, and the MUs while systematically analyzing the three-stage decision processes. By adopting the firefly learning mechanism and the iterative RBS, each individual network agent attempts to maximize its own revenue based on the dual-leader Stackelberg game model. The major novelty of our proposed game model is its feasibility and flexible self-adaptability for system dynamics in providing a desirable solution in the *data sponsoring* operations. The main steps of the proposed scheme are described as follows:

Step 1. System factors and control coefficients are determined by the simulation scenario in Section 3 (see simulation assumptions and Table 2).

Step 2. To provision the *data sponsoring* in data services, three-stage decision processes are sequentially executed at each time period, $\mathfrak{H}_t$, of the game.

Step 3. At the first stage, the CP and the SP individually select their strategies based on the firefly learning algorithm. Using equations (2) and (3), each strategy's selection probability is estimated, and the CP and the SP decide their strategies to maximize their utility functions stochastically, which are defined in equation (1).

Step 4. At the second stage, the MUs deal with the problem of maximizing their utility functions. In a noncooperative fashion, each MU selects their strategy, ϕ, independently, to satisfy equation (4).

Step 5. At the third stage, the leaders, i.e., the CP and the SP, can reach a fair-efficient agreement to split the profit gained based on the RBS. Leaders periodically adjust their bargaining powers, i.e., δ_{CP} and δ_{SP}, by using equation (7) while modifying their weight factors, i.e., $\mathscr{J}_{\mathrm{CP}}$ and $\mathscr{J}_{\mathrm{SP}}$, by using equation (8).

Step 6. The profit is shared between the CP and the SP according to equations (5) and (6). As leaders, they coordinately interact with each other and find the most fair-efficient solution in a cooperative manner.

Step 7. For each time period, $\mathfrak{H}_t$, the game players in our dual-leader Stackelberg game model are constantly self-monitoring the *data sponsoring* system; proceed to Step 3 for the next game iteration.

3. Simulation Results and Discussion

To evaluate the performance of the proposed scheme, we develop a simulation model and conduct extensive experiments. We verify the performance superiority of our approach by comparing it to the existing *SMDC* [8], *CDSC* [7], and *HGDS* [13] schemes. To ensure a fair comparison, we have considered the following simulation assumptions and scenarios:

(i) The simulated *data sponsoring* system consists of one CP, five SPs, and 100 MUs; MUs are randomly distributed in the cellular area.

(ii) To represent various MU application services, four different types of multimedia data are assumed, based on their data consumption. They are generated with equal probability.

(iii) Data consuming request rate per MU is represented by Poisson process (ρ). The offered rate range is varied from 0 to 3.0.

(iv) Total bandwidth capacity in each SP is 100 Tbps.

(v) The CP's advertisement revenue increases linearly in proportion to the amount of data consumed.

(vi) Network performance measures obtained on the basis of 100 simulation runs are plotted as functions of the offered data service request rate (ρ).

Table 2: System parameters used in the simulation experiments.

Traffic type	Application	Bandwidth request	Connection duration average
I	A group applications	1.2 Gbps	300 sec (5 min)
II	B group applications	1.4 Gbps	180 sec (3 min)
III	C group applications	1.6 Gbps	360 sec (6 min)
IV	D group applications	1.8 Gbps	480 sec (8 min)
Parameter	*Value*	*Description*	
n	5	The number of SPs	
m	100	The number of MUs	
$[\mathfrak{B}^{\mathrm{CP}}_{\min} \cdots \mathfrak{B}^{\mathrm{CP}}_{j} \cdots \mathfrak{B}^{\mathrm{CP}}_{\max}]$	0.1, 0.2, 0.3, 0.4, 0.5	Data sponsoring rate strategies by the CP (min = 1, max = 5)	
$[\mathfrak{Z}^{\mathrm{SP}}_{\min} \cdots \mathfrak{Z}^{\mathrm{SP}}_{k} \cdots \mathfrak{Z}^{\mathrm{SP}}_{\max}]$	0.4, 0.6, 0.8, 1, 1.1	Price strategies per data bit by the SP (min = 1, max = 5)	
r^{SP}_{s}	0.5	A cost factor for the data service of the SP	
α^{CP}, ε	0.01, 0.5	Regulating parameters for the randomized searching	
η	0.6	The CP's fixed unit price per bit for the data provisioning	
$\mathscr{R}^{\mathrm{CP}}$	0.5	The advertisement revenue rate per data consuming	
β^{CP}	0.9	The attractiveness when the difference propensities	
γ	1	A coefficient to control the convergence rate	
ϑ	2	The MU's satisfaction adjustment factor	
Δ	10	The fixed time period of negotiation round	

(vii) The performance criteria obtained through the simulation are system throughput, leaders' profit-sharing fairness, and user participation ratio.

(viii) We assume the absence of physical obstacles in the experiments.

Table 2 shows the simulation parameters and the types of multimedia data traffic used in the simulation. Simulation parameters are chosen to make the simulation feasible. Each data application has different characteristics with respect to different types of traffic. Using these parameters and control factors, the *data sponsoring* system performance is evaluated under different data service request rates.

Even though the existing *SMDC* [8], *CDSC* [7], and *HGDS* [13] schemes dynamically control the *data sponsoring* system, they have several disadvantages. First, these existing schemes rely on assumptions that are impractical for real operations. Control algorithms based on inapplicable presumptions can potentially lead to erroneous decisions. Second, these schemes cannot adaptively estimate the current network conditions. Third, these schemes operate the network system by some fixed system parameters. Under dynamic network environments, they are inappropriate approaches to the operation of real-world network systems.

In Figure 1, we observe the relationship between the system throughput of the schemes and the offered data service request rates. In general terms, the system throughput is the sum of the data transmission rates that are delivered to all MUs in a network. It is essentially synonymous to digital bandwidth consumption. In our experiments, we normalize the system throughput of each scheme to achieve a fair comparison. The system throughput may be affected by the behavior of the MUs. The system throughput increases along with the growing rate of service requests; it is intuitively correct. In our scheme, the MUs give a useful feedback to the CP and the SP in accordance with the game-based decision mechanism. Therefore, the CP and the SP can adaptively adjust their service prices to effectively recruit as many data consuming MUs as possible. The simulation results clearly show that, on average, the proposed scheme offers the superiority of maintaining a stable throughput under different data service rate intensities.

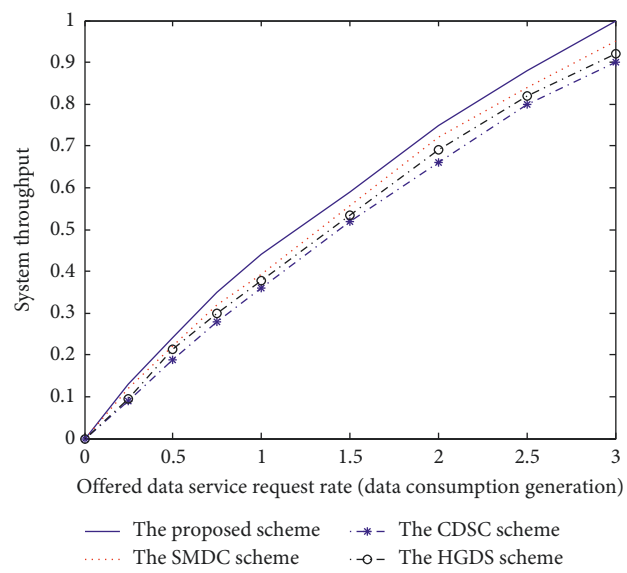

Figure 1: System throughput.

The fairness of profit sharing between the CP and the SP is shown in Figure 2. In the *data sponsoring* system infrastructure, the CP and the SP work as dual service supervisors. Therefore, fairness is a prominent issue for the operations of the CP and the SP. To characterize the fairness notion, we follow Jain's fairness index, which has been frequently used to measure the fairness in network management. In the proposed scheme, we develop a novel dual-leader Stackelberg game model, and the leaders, i.e., the CP and the SP, share the profit fairly based on the RBS, which had been developed focusing on the profit distribution to the game players. Therefore, in our scheme, the profit is fairly dealt out between the CP and the SP. As shown in Figure 2,

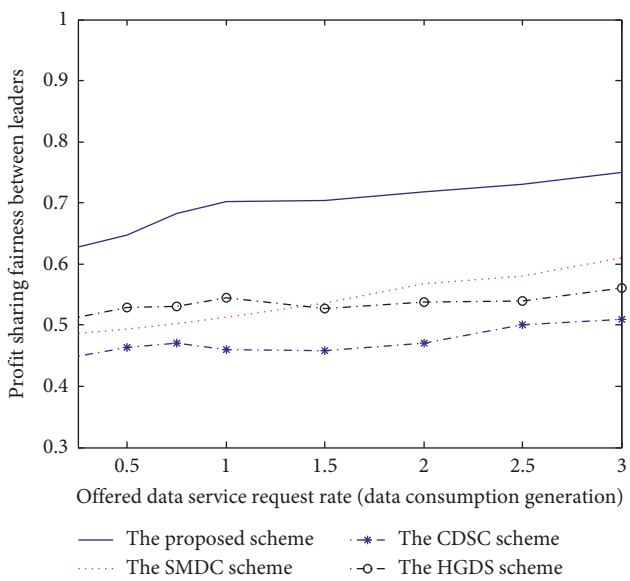

Figure 2: Profit-sharing fairness between CP and SP.

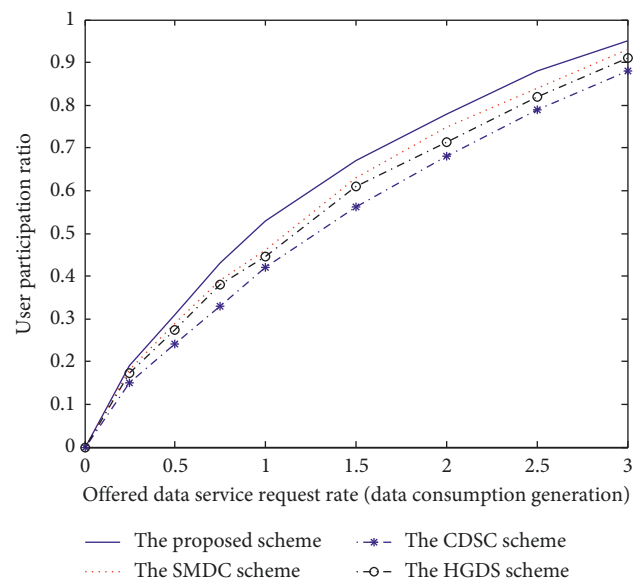

Figure 3: User participation ratio.

the profit-sharing fairness in the proposed scheme is distinctly better compared to the existing schemes.

Considering the user's selfishness, we observe the user participation ratios of the schemes in Figure 3. The user participation ratios of all the schemes are similar to each other, and the performance trend is similar to the system throughput. However, the proposed scheme is developed to induce selfish MUs to use the data consuming services, by the effective *data sponsoring* technique. Under the constantly changing environment, we can align the goals of selfish individual MUs and obtain their active service participations. Therefore, as can be seen in Figure 3, the proposed scheme can effectively recruit MUs and outperform the existing methods in this performance measure from low to high data service request intensities.

The simulation results shown in Figures 1–3 demonstrate that the proposed scheme has a good performance stability while maintaining better system performance in terms of system throughput, profit-sharing fairness, and user participation ratio. In contrast, the *SMDC*, *CDSC*, and *HGDS* schemes cannot offer this fascinating outcome under widely different data service request intensities.

4. Summary and Conclusions

Recently, the *data sponsoring* technique has been introduced in the mobile data market, allowing CPs to subsidize MUs' data costs. As sponsored data gain traction in the industry, it is important to understand their implications for CPs, SPs, and MUs. In this work, we tackle the *data sponsoring* problem in 5G networks and design a new *data sponsoring* control scheme based on the dual-leader Stackelberg game model. First, we derive the leader's price decision algorithm using the firefly learning method. Then, the MU reaction procedure is defined; individual MU attempts to maximize their payoffs in a distributed and noncooperative game manner. Finally, the profit-sharing problem between the CP and the SP is formulated according to the RBS. Control decisions of the CP, the SP, and MUs are coupled with each other, and they pursue mutual advantages. Therefore, the result of the others' decisions becomes the input to an entity's decision process. This feedback-based iterative game process continues until the best solution is obtained. Through the extensive simulation analysis, it has been verified that our proposed scheme can improve the performance in terms of system throughput, profit-sharing fairness, and user participation ratio, compared to the existing schemes.

For future research, there are various open issues and practical challenges to be considered for the *data sponsoring* operations. First, we would like to consider privacy issues such as the differential privacy during the *data sponsoring* operation. Another direction for future work is to include theoretical interpretations for optimal solutions. In addition, we plan to jointly control the energy scheduling and the transmission power of MUs' devices. We also feel that an adaptive and cost-efficient data center network management for the *data sponsoring* system will become increasingly important in the future.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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