Analysis of Interactions Among ISPs in Information Centric Network with Advertiser Involvement

Hamid Garmani, Mohamed El Amrani, Driss Ait Omar, Mohamed Baslam, and Hicham Zougagh

Abstract—**In response to the escalating volume of Internet traffic, scalability challenges have emerged in content delivery. Information-Centric Networking (ICN) has emerged as a solution to accommodate this surge in traffic by leveraging caching. Collaborative caching within ICN is pivotal for enhancing network performance and reducing content distribution costs. However, current pricing strategies on the Internet do not align with ICN interconnection incentives. This paper delves into the economic incentive caching of free content among various types of ICN providers, including advertisers and Internet service providers (ISPs). Specifically, we employ game-theoretic models to analyze the interaction between providers within an ICN framework, where providers are incentivized to cache and share content. Content popularity is modeled using a generalized Zipf distribution. We formulate the interactions among ISPs as a non-cooperative game and, through mathematical analysis, establish the existence and uniqueness of the Nash equilibrium under certain conditions. Additionally, we propose an iterative and distributed algorithm based on best response dynamics to converge towards the equilibrium point. Numerical simulations demonstrate that our proposed game models yield a win-win solution, showcasing the effectiveness of our approach in incentivizing collaborative caching of free content within ICN.**

Index Terms—**Pricing, ICN, ISP, Caching, advertisers, Nash equilibrium, Game Theory.**

I. Introduction

Since its inception in the 1960s, the Internet has increasingly become integral to people's lives. Currently, the predominant mode of content delivery involves distributing content from a single source to multiple users (similar to multicast), facilitating the dissemination of multimedia files from creators (such as Netflix, IPTV, and various websites) and the sharing of user-generated content on platforms like Facebook, Weibo, YouTube, and Youku. The exponential growth in users and service demands has led to significant improvements in the backbone network infrastructure, including the deployment of numerous routers, high-speed transmission technologies, and private network systems. These enhancements aim to achieve more efficient data delivery across the Internet [1].

Traditionally, content delivery has relied on the client-server model. However, a key solution that offers superior performance in terms of lower access latency, higher data transfer rates, and reduced costs compared to the client-server model involves moving content from the original server to the edge of the Internet, known as a local replica server. A prime example of this approach is the Content Delivery Network (CDN) using IP multicast, which addresses the core challenge of Internet infrastructure [2]. CDN works by distributing content from the original server to end-users via replica servers strategically placed across the network, alleviating backbone network congestion and enhancing service quality. Content stored and served through replica servers is meticulously selected to achieve near 100% hit rates in some instances. Consequently, CDN implementation can significantly reduce access delays, boost content distribution rates, and minimize network bandwidth utilization [3][4][5].

As network traffic continues to escalate and quality of service (QoS) demands become more complex, maintaining optimal CDN performance has become costly due to the need for a large number of edge servers and ongoing operational expenses [6]. Additionally, the agility of server deployment is limited, resulting in prolonged setup times and challenges in selecting appropriate locations with sufficient capacities. A significant drawback of CDN is the lack of real-time network condition information, leading to suboptimal user assignment decisions and exacerbating network bottlenecks [7][8]. The rapid surge in network traffic has strained existing CDN systems, highlighting limitations in IT infrastructure and storage space availability.

ICN is gaining momentum as a prospective Internet framework, representing a departure from host-centric communication towards user-driven data retrieval [9]. Its inception can be traced back to TRIAC, as proposed by Cheriton and Gritter in 2000. Subsequent advancements include the development of Data-Oriented Network Architecture (DONA) by [10]. Related technologies such as Content-Centric Networking (CCN) and Named Data Networking (NDN) complement ICN's objectives. In ICN, users prioritize the content itself over its origin [11]. This stems from a recognition that contemporary Internet usage increasingly emphasizes data dissemination rather than host-to-host communication. ICN thus aims to address this trend by offering a new, more efficient model. Interest-oriented networking within ICN utilizes dynamic content caching at the network layer, facilitating reliable and scalable content delivery. This approach accelerates the timely provision of information to end-users. However, there are diverse approaches to ICN distribution strategies, with ongoing research exploring various means to overcome additional challenges in Internet architecture, such as mobility management and security enforcement [12]. A fundamental aspect of ICN is its

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utilization of in-network caching to enhance the efficiency of content dissemination and information retrieval across network entities. From a caching perspective, ICN cache exhibits distinct characteristics such as transparency to applications, ubiquity, and fine-grained content caching, setting it apart from conventional Web and CDN caching methods [13][14][15].

In-network caching is recognized for its potential to yield advantages for users, ISPs, and content providers (CPs). By caching content on nearby routers, users can experience reduced delays in accessing content, consequently enhancing their overall quality of experience. Viewed from the ISP's standpoint, in-network caching offers the benefit of reducing outgoing traffic directed towards neighboring ISPs or content providers, thereby decreasing overall bandwidth consumption. Consequently, studies [16][17][18] advocate for ISPs to implement infrastructures equipped with built-in caching capabilities. Furthermore, for content providers, fulfilling requests from the on-path caching router can alleviate the burden on the content provider, conserve bandwidth resources, and mitigate network congestion. Particularly noteworthy is that in situations where the content provider experiences temporary downtime, the network's built-in content store can continue delivering content to users, thereby bolstering the network's resilience to some extent.

Given the pivotal role of in-network caching in ICN, scholars have devoted considerable attention to content caching and distribution. A key consensus emphasizes the necessity for various ICNs to collaborate to enhance overall network performance. However, due to the self-interested nature of ICN entities (such as ISPs and CPs), these entities may refrain from caching or forwarding data, and ISPs may hesitate to deploy ICN if profitability is not assured. Therefore, to promote content distribution and sharing, it becomes imperative to identify a suitable win-win economic model that benefits all entities involved.

In this study, we delve into caching free content, alongside pricing and Quality of Service (QoS) strategies adopted by ISPs, leveraging insights from content popularity. We explore Nash strategies within a non-cooperative game framework among the aforementioned entities, utilizing a probabilistic model that assumes users' requests conform to the generalized Zipf distribution.

Our analysis rigorously establishes the existence and uniqueness of Nash equilibrium in this non-cooperative game among ISPs. This equilibrium signifies a stable state wherein ISPs lack incentives to alter their strategies. Thus, our model not only offers economic incentives for caching content but also ensures the stability of the economy and fosters economic growth. We substantiate our analysis with numerical results demonstrating the mutual benefits accrued by both ISPs and users through caching investment. These findings underscore the viability of our approach in fostering symbiotic relationships within the caching ecosystem.

The remainder of this paper is structured as follows. Section 2 provides an overview of related research. In Section 3, we delineate the system model employed in our study. Section 4 is dedicated to formulating and analyzing the non-cooperative game under consideration. Subsequently, Section 5 presents the numerical results derived from our analysis. Finally, Section 6 offers conclusions drawn from our findings.

II. Related Work

The existing literature has investigated various issues pertaining to caching within small cell networks, cloud radio access networks, CPs, and ISPs. The authors in [19] introduced two strategies for uplink transmission in distributed Beyond Fifth Generation small cell networks. The initial scheme prioritizes content matching to eradicate duplicate contents within distributed caches. Meanwhile, the second scheme reallocates non-duplicated cached contents among distributed caches, considering their available space and content size. These methods target boosting energy and spectral efficiency by minimizing redundant uploads and optimizing distributed content caching. Ultimately, the goal is to enhance content delivery efficiency. In [20] the authors presented a cooperative caching strategy leveraging mobile prediction, and social awareness to enable collaborative content decision-making among edge devices. They utilized the long short-term memory network to forecast vehicle trajectories, calculate social relationships through content similarity and contact rates among vehicle users to identify potential caching nodes, and employ deep reinforcement learning to determine the ultimate caching decision. In [21] the authors introduced a content-centric network-based content transfer strategy tailored for the vehicle-to-grid network. Specifically, they leveraged the mobility patterns of Electric Vehicles to capture inter-contact times between node pairs and devised a caching placement scheme aimed at maximizing the content offloading ratio.

The authors in [22] tackled the vehicular service caching issue by leveraging vehicle surroundings' function-features and transportation correlations. Initially, they utilized these features to estimate service preferences, ensuring high hit ratios for cached services. Subsequently, they framed the vehicular service caching problem as a constrained optimization challenge and devised a collaboration mechanism among Roadside Units, utilizing transportation correlations from vehicle trajectories. Finally, they introduced two vehicular service caching techniques based on Gibbs sampling to optimize network delays for vehicular services and mitigate the adverse effects of vehicle mobility. The authors in [23] introduced a labeled graph partitioning scheme for distributed edge caching, which hinges on frequent query patterns. This scheme first generates frequent query patterns from users' historical query subgraphs and then conducts labeled graph partitioning based on these patterns. This ensures that the resulting labeled graph, divided among edge servers, optimally serves frequent user queries while maintaining a minimum edge cut. In [24] the authors introduced a collaborative caching strategy employing federated learning. Initially, federated learning is employed to predict user preferences across distributed nodes, enabling the development of an efficient content caching policy. Subsequently, the allocation of caching resources to optimize video provider costs is framed as a Markov decision process, and a reinforcement learning approach is utilized to optimize caching decisions. The authors in [25] proposed a video caching and transcoding strategy for delay-constrained content delivery in multi-tier wireless networks. Particularly for multimedia services whose content can be encoded into multiple quality versions and consists of multiple chunks, they presented an approach of caching chunks of an identical file separately in different network layers with different qualities. The authors decomposed the joint optimization problem into caching and transcoding subproblems.

The authors in [26] developed a model considering the preferences of both service providers and requesters to optimize cache content sharing via content-centric network communications. They formulated a decentralized matching problem incorporating the joint transmit power of both content providers and requesters. Lastly, the authors introduce a distributed blind matching algorithm, implemented through a smart contract deployed on the Ethereum network, thereby eliminating the need for an intermediary authority. In [27] the authors explored the dynamic allocation of cache resources and price determination problem within a caching system comprising multiple content producers as buyers and multiple competing ICN cache providers as sellers of caching resources. They introduced a novel reverse auction-based caching and pricing scheme designed to maximize the caching benefits for content producers. The authors in [28] suggest an economic pricing strategy to tackle caching resource management challenges in 5G wireless networks, aiming to address limitations in throughput, latency, and reliability. Furthermore, they explore this approach through an oligopolistic multi-market framework derived from Cournot, Stackelberg, and Bertrand models. In [29] the authors explored the utilization of an in-network caching model involving multiple CPs. They investigated the collective objective of maximizing CPs' profits and increasing their market share to capture a substantial customer base. This problem is modeled as a non-cooperative game among the CPs. The authors in [30] delve into the dynamics between users, ISPs, and CPs. Then they scrutinize the caching and pricing strategies employed by each entity within the context of Nash equilibrium. By comparing and analyzing these strategies, they aimed to determine which charging model best aligns with the requirements of network entities in the ICN environment. In [31] the authors delve into a non-cooperative game involving an ISP and a CP. Within this framework, the ISP adjusts its caching strategy while the CP can influence its pricing strategy. They notably highlight that the direction of the side-payment (from the ISP to the CP) in an ICN setup differs from that in the existing Internet model, which follows a host-centric communication model. The authors in [32] proposed an examination of the dynamic interactions within a duopoly model featuring two ISPs. The competition between these ISPs revolves around their pricing strategies and the quantity of cached items, with both entities characterized as bounded rational. In [33] the authors investigated and analyzed the non-cooperative game dynamics between ISPs and CPs within the context of ICN. They proposed establishing peering links between access ISPs to facilitate collaborative caching. Their findings indicate that cache allocation can be reasonably managed based on end-user demand, allowing each entity to determine an optimal pricing strategy according to its equilibrium point. The authors in [16] characterized content popularity using the generalized Zipf distribution and employed a non-cooperative game framework to determine caching and pricing strategies.

From a technical standpoint, ICN presents considerable potential as a future network architecture. The successful deployment of ICN hinges on the development of effective pricing and caching mechanisms. While most existing research has primarily focused on caching paid content, where ISPs generate revenue from both network and content access, our study fills a gap by exploring pricing and caching strategies for free content. Using game theory and Nash equilibrium, we analyze these interactions. Furthermore, our research introduces an advertiser model to investigate the economic dynamics between advertisers and ISPs, where ISPs earn revenue from advertisers and network access. This approach offers a novel perspective by concentrating on free content and the role of advertisers, providing insights that extend beyond previous studies.

III. Problem Modeling

We examine a streamlined networking market featuring a single CP, N ISPs, and a considerable number of users. In this setup, all users can exclusively access the CP content through the network infrastructure offered by their respective ISP, with the CP serving as the content source for the users. Figure 1 illustrates the financial transactions among diverse entities at different price points. The network economy relies on three key factors: pricing, caching, and QoS. Assuming that each ISP has access to all content, it can choose to cache either the entire requested content or a portion of it. Consider L as the quantity of items sold by the CP. The caching strategy implemented by each ISP is represented by k_{il}, where it assumes a value of 1 if ISP_i opts to cache item l, and 0 if ISP_i chooses not to cache item l. Each ISP_i establishes two distinct prices: (1) the network price per unit of data p_{s_j}, for transporting the content to users; and (2) price per attention $p_{a_{il}}$ for advertising within the cached content. Each ISP_i assigns a bandwidth Ψ_i and promotes a QoS q_{s_i} to users. In representing user behavior, we have assumed that the demand for content at each ISP is a linear function of the strategies employed by all ISPs. A detailed summary of notations is presented in Table I.

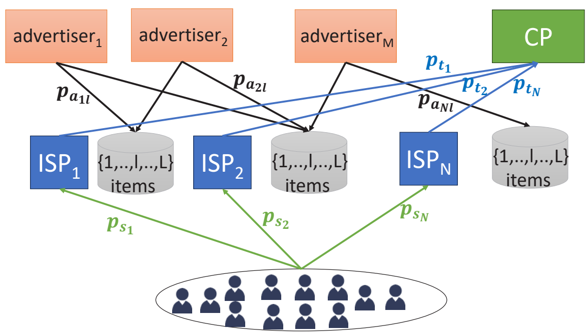

Fig. 1. Model architecture.

TABLE I
SUMMARY OF NOTATION.

Notation	Description
N	Number of ISPs.
L	The number of items the CP would sell.
L_i	Number of items that the CP sells to ISP_i.
M_{il}	Number of advertisers for item l in ISP_i cache.
B_{il}	Budget over a specified time frame (such as daily, weekly, or monthly).
v_{il}	Valuation assigned by advertisers for item l, representing their willingness to pay for ISP_i advertisement slots.
$\bar{v}_{il}$	Maximum value of v_{il}.
p_{s_i}	Network access price of ISP_i.
$p_{a_{il}}$	Price charged per attention by the ISP_i for item l.
q_{s_i}	Quality of service (QoS) of ISP_i.
$D_{a_{il}}$	Demand for attention from advertisers to the ISP_i for item l.
C_{il}	Cost paid by ISP_i for caching item l.
γ_i	Backhaul bandwidth cost of ISP_i.
p_{t_i}	Fee that the ISP_i pays to the CP when requesting content from it.
α_i^j	Sensitivity of ISP_i to price p_{s_j} of ISP_j.
β_i^j	Sensitivity of ISP_i to QoS q_{s_j} of ISP_j.
d_i	Total potential demand of users of ISP_i.
D_i	Demand of ISP_i.
Ψ_i	Backhaul bandwidth of ISP_i.
l^η	Rank of item l.
η	Skewness of the popularity distribution.
χ_{il}	Non-negative constant.
k_{il}	The caching strategy implemented by each ISP, where $k_{il} = 1$ if ISP_i opts to cache item l, and $k_{il} = 0$ if ISP_i chooses not to cache item l.
ISP	Internet Service Provider.
CP	Content provider.

A. Content Popularity

Let L denote the total number of free items provided by CPs, with each item characterized by a measure of popularity represented by the probability of requests for it. We adopt a model where the popularity of content remains uniform across all users. As observed in prior studies (e.g., [34] [35]), we model the probability of requests using the generalized Zipf distribution function, defined as follows:

$$\phi_l = A^{-1} l^{-\eta} \tag{1}$$

where $A = \sum_{l=1}^{L} l^{-\eta}$, $l^{-\eta}$ is the rank of item $l - th$, and η is the skewness of the popularity distribution. Each item is ranked according to their popularity, with item l representing the $l - th$ most popular item, where $l = 1$ denotes the most popular item, and $l = L$ represents the least popular item. The reason we have used the generalized Zipf distribution function is twofold: (1) experimental results show a reasonable fit to the Zipf model, and (2) the generalized Zipf distribution function offers analytical tractability [16].

B. Demand model

We define D_i as the average demand from all users for service of ISP_i. The demand D_i is a linear function of the strategies employed by all ISPs. The linearity means that the relationship between the demand and strategies is proportional, i.e., a change in strategy will result in a directly proportional change in demand. This simplifies the mathematical representation of the interactions between ISPs, making it easier to model their competitive behavior. However, this simplification is common in economic models to focus on strategic interactions without the complexities of nonlinear demand. In addtion, most paper in the literature model the demande as a liniear function ([36], [37], [16]). The demand D_i is influenced by various factors including price p_{s_i}, and QoS q_{s_i}. Additionally, the demand function is affected by the competitive landscape, taking into account the prices p_{s_j} and QoS q_{s_j}, $j \neq i$ offered by ISP_j rivals of ISP_i . Ultimately, D_i diminishes as the price p_{s_i} rise, and grows with an increase in the prices p_{s_j} for $j \neq i$. Conversely, it escalates with an enhancement in QoS q_{s_i}, and declines in response to an increase in QoS q_{s_j} for $j \neq i$.

Subsequently, the demand functions D_i are formulated as follows:

$$D_i = d_i - \alpha_i^i p_{s_i} + \beta_i^i q_{s_i} + \sum_{j=1, j \neq i}^{N} \left(\alpha_i^j p_{s_j} - \beta_i^j q_{s_j} \right) \tag{2}$$

where d_i represents the potential demand from users. Here, α_i^j and β_i^j are positive constants that denote, respectively, ISP_j sensitivity to the price and the QoS offered by ISP_j.

Assumption 1 *The sensitivity α verifies:*

$$\alpha_i^i \geq \sum_{j=1, j \neq i}^{N} \alpha_i^j \tag{3}$$

The sensitivity β verifies:

$$\beta_i^i \geq \sum_{j=1, j \neq i}^{N} \beta_i^j \tag{4}$$

Assumption 1 is essential to guarantee the uniqueness of the Nash equilibrium.

This paragraph delineates the economic interactions between advertisers and the ISP_i concerning the content stored in their cache. It discusses a scenario where there are M_{il} advertisers for item l, each operating with a predetermined budget B_{il} over a specified time frame (such as daily, weekly, or monthly). Additionally, advertisers assign a valuation v_{il} of item l, representing their willingness to pay for ISP_i advertisement slots. The valuation v_{il} of advertisers for item l is typically considered private information, making it difficult to ascertain. However, we make the assumption that we possess knowledge of the probability density function of advertisers' valuations, denoted as $x(v_{il})$, defined over the domain $[0, \bar{v}_{il}]$. Correspondingly, the cumulative distribution function is denoted as $X(v_{il})$. Additionally, we assume that the valuations of all advertisers are independent and identically distributed. Let $p_{a_{il}}$ represent the price charged per attention by the ISP_i for item l. We define $D_{a_{il}}$ as the demand for attention from advertisers to the ISP_i for item l. Therefore, $D_{a_{il}}$ can be represented as follows [38]:

$$D_{a_{il}} = \frac{M_{il} B_{il}}{p_{a_{il}}} prob(v_{il} \geq p_{a_{il}}) \tag{5}$$

with $prob(v_{il} \geq p_{a_{il}}) = 1 - X(p_{a_{il}})$

$$D_{a_{il}} = \frac{M_{il} B_{il}}{p_{a_{il}}} (1 - X(p_{a_{il}})) \tag{6}$$

We assume that v_{il} adheres to a uniform distribution within the $[0, \overline{v}_{il}]$ range. This means that every value within the range $[0, \overline{v}_{il}]$ is equally likely. In this case, v_{il} can take any value between 0 and $\overline{v}_{il}$, with no preference for one value over another. By assuming a uniform distribution, the model becomes easier to work with mathematically. Uniform distributions often lead to more straightforward calculations and analyses compared to more complex or skewed distributions.

This assumption leads us to derive the expression for the cumulative distribution function $X(p_{a_{il}})$ as

$$X(p_{a_{il}}) = \frac{p_{a_{il}}}{\overline{v}_{il}} \tag{7}$$

Subsequently, the demand $D_{a_{il}}$ takes the following form:

$$D_{a_{il}} = \frac{M_{il}B_{il}}{p_{a_{il}}}(1 - \frac{p_{a_{il}}}{\overline{v}_{il}}) \tag{8}$$

The optimal price $p_{a_{il}}$, is achieved when $D_{a_{il}} = (1 + \chi_{il}k_{il})\phi_l D_i$:

$$\sum_{l=1}^{L_i}(1 + \chi_{il}k_{il})\phi_l D_i = \frac{M_{il}B_{il}}{p_{a_{il}}}\left(1 - \frac{p_{a_{il}}}{\overline{v}_{il}}\right) \tag{9}$$

Then

$$p_{a_{il}} = \frac{M_{il}B_{il}\overline{v}_{il}}{M_{il}B_{il} + \sum\limits_{l=1}^{L_i}(1 + \chi_{il}k_{il})\phi_l D_i \overline{v}_{il}} \tag{10}$$

C. Utility

The net profit for ISP_i is essentially the contrast between the total revenue and the fee paid:

$$\begin{aligned} U_i =& p_{s_i}\sum_{l=1}^{L_i}(1 + \chi_{il}k_{il})D_i + \sum_{l=1}^{L_i}\phi_l[k_{il}p_{a_{il}}D_{a_{il}} \\ & - p_{t_i}D_i(1 - k_{il}) - C_{il}k_{il}(1 + \chi_{il}k_{il})D_i] \\ & - \gamma_i(L_i - \sum_{l=1}^{L_i}k_{il})\Psi_i \end{aligned} \tag{11}$$

where $p_{s_i}\sum_{l=1}^{L_i}(1 + \chi_{il}k_{il})D_i$ is the income generated from network access. Recall that caching may serve as an incentive to increase content consumption. The new content demand, denoted as $(1 + \chi_{il}k_{il})D_i$, is influenced by the proportion of cached content. The term $\chi_{il}k_{il}$ represents the variation in demand for the content from the ISP cache. C_{il} represents the cost associated with caching item l. p_{t_i} is the fee that the ISP remits to the CP when seeking content, as the direction of the side-payment (from the ISP to the CP) in an ICN differs fundamentally from the current Internet model. $\sum_{l=1}^{L_i}\phi_l k_{il}p_{a_{il}}D_{a_{il}}$ is the revenue of ISP_i from advertisers. $\sum_{l=1}^{L_i}\phi_l p_{t_i}(1 + \chi_{il}k_{il})D_i(1 - k_{il})$ is the transmission fee. $C_{il}k_{il}(1 + \chi_{il}k_{il})D_i$ is the caching cost. γ_i represents the cost of unit backhaul bandwidth paid by ISP_i. Ψ_i denotes the backhaul bandwidth necessary to fulfill demand D_i. $(L_i - \sum_{l=1}^{L_i}k_{il})\Psi_i$ is the backhaul bandwidth indispensable for meeting the demand $(L_i - \sum_{l=1}^{L_i}k_{il})D_i$. We present the QoS as the expected delay, which is computed using the Kleinrock function corresponding to the delay in an M/M/1 queue with FIFO discipline or an M/G/1 queue under processor sharing, as described in [36]. Similar to [36], instead of using the actual delay, we consider its reciprocal of its square root :

$$q_{s_i} = \frac{1}{\sqrt{Delay_i}} = \sqrt{\Psi_i - \sum_{l=1}^{L_i}(1 + \chi_{il}k_{il})D_i} \tag{12}$$

signifying that

$$\Psi_i = q_{s_i}^2 + \sum_{l=1}^{L_i}(1 + \chi_{il}k_{il})D_i \tag{13}$$

By substituting equations (10) and (13) into equation (11), the utility of ISP_i becomes:

$$\begin{aligned} U_i =& p_{s_i}\sum_{l=1}^{L_i}(1 + \chi_{il}k_{il})D_i + \sum_{l=1}^{L_i}\phi_l \\ & [\frac{B_{il}M_{il}\overline{v}_{il}k_{il}(1 + \chi_{il}k_{il})\phi_l D_i}{B_{il}M_{il} + \sum\limits_{l=1}^{L_i}(1 + \chi_{il}k_{il})\phi_l D_i\overline{v}_{il}} \\ & - p_{t_i}(1 + \chi_{il}k_{il})D_i(1 - k_{il}) - C_{il}k_{il}(1 + \chi_{il}k_{il})D_i] \\ & - \gamma_i(L_i - \sum_{l=1}^{L_i}k_{il})\left(q_{s_i}^2 + \sum_{l=1}^{L_i}(1 + \chi_{il}k_{il})D_i\right) \end{aligned} \tag{14}$$

IV. GAMES FORMULATION

The non-cooperative price QoS game is $G = [\mathscr{N}, \{\mathscr{P}_{s_i}, \mathscr{Q}_{s_i}\}, \{U_i(.)\}]$, where $\mathscr{N} = \{1, ..., N\}$ is the set of ISPs, $\mathscr{P}_{s_i}$ is the price strategy set of ISP_i and $\mathscr{Q}_{s_i}$ is the QoS strategy set of ISP_i. The strategy spaces $\mathscr{P}_{s_i}$ and $\mathscr{Q}_{s_i}$ are compact and convex sets. Thus, $\mathscr{P}_{s_i} = \left[\underline{p}_{s_i}, \overline{p}_{s_i}\right]$ and $\mathscr{Q}_{s_i} = \left[\underline{q}_{s_i}, \overline{q}_{s_i}\right]$. Let the price vector $\mathbf{p}_s = (p_{s_1}, ..., p_{s_N})^T \in \mathscr{P}_s^N = \mathscr{P}_{s_1} \times \mathscr{P}_{s_2} \times ... \times \mathscr{P}_{s_N}$, QoS vector $\mathbf{q}_s = (q_{s_1}, ..., q_{s_N})^T \in Q_s^N = \mathscr{Q}_{s_1} \times \mathscr{Q}_{s_2} \times ... \times \mathscr{Q}_{s_N}$.

Considering rationality of service providers, the Nash equilibrium concept is the natural concept solution of the non-cooperative price QoS game. We first will investigate the Nash equilibrium solution for the induced game as defined in the previous section. We will show that a Nash equilibrium solution exists and is unique by using the theory of concave games [39]. We recall that a non-cooperative game G is called concave if all players' utility functions are strictly concave with respect to their corresponding strategies [39].

According to [39] a Nash equilibrium exists in a concave game if the joint strategy space is compact and convex, and the utility function that any given player seeks to maximize is concave in its own strategy and continuous at every point in the product strategy space. Formally, if the weighted sum of the utility functions with non-negative weights:

$$\Xi = \sum_{i=1}^{N}x_i U_i \tag{15}$$

is diagonally strictly concave, this implies that the Nash equilibrium point is unique. The notion of diagonal strict concavity means that an individual user has more control over its utility function than the other users have on it, and is proven using the pseudo-gradient of the weighted sum of utility functions, [39].

Acoriding to [40] if a concave game fulfills the dominance solvability condition:

$$-\frac{\partial^2 U_i}{\partial p_{s_i}^2} - \sum_{j=1, j\neq i}^{N} \left| \frac{\partial^2 U_i}{\partial p_{s_i} \partial p_{s_j}} \right| \geq 0 \tag{16}$$

the non-cooperative game G admits a unique Nash equilibrium.

A. Price game

The game G in price is defined for fixed $\mathbf{q}_s \in \mathscr{Q}_s$ as $G(\mathbf{q}_s) = [\mathscr{N}, \{\mathscr{P}_{s_i}\}, \{U_i(., \mathbf{q}_s)\}]$.

Definition 1 *A price vector $\mathbf{p}_s^* = (p_{s_1}^*, ..., p_{s_N}^*)$ is a Nash equilibrium of the game $G(\mathbf{q}_s)$ if:*

$$\forall (i, p_{s_i}) \in (\mathscr{N}, \mathscr{P}_{s_i}), U_i(p_{s_i}^*, \mathbf{p}_{s_{-i}}^*, \mathbf{q}_s) \geq U_i(p_{s_i}, \mathbf{p}_{s_{-i}}^*, \mathbf{q}_s)$$

Theorem 1 *For each $\mathbf{q}_s \in \mathscr{Q}_s$, the game $[\mathscr{N}, \{\mathscr{P}_{s_i}\}, \{U_i(., \mathbf{q}_s)\}]$ admit a unique Nash Equilibrium.*

The second order derivative of the utility with respect to the prices is :

$$\begin{aligned} \frac{\partial^2 U_i}{\partial p_{s_i}^2} &= -2\alpha_i^i \sum_{l=1}^{L_i} (1 + \chi_{il} k_{il}) \\ &- \sum_{l=1}^{L_i} \phi_l \left[\frac{2(\alpha_i^i)^2 B_{il}^2 M_{il}^2 \overline{v}_{il}^2 k_{il}^2 (1 + \chi_{il} k_{il})^2 \phi_l^2}{\left(B_{il} M_{il} + \sum\limits_{l=1}^{L_i} (1 + \chi_{il} k_{il}) \phi_l D_i \overline{v}_{il} \right)^3} \right] \leq 0 \end{aligned} \tag{17}$$

The second derivative of U_i is consistently negative, it signifies the concavity of U_i and, consequently, assures the existence of a Nash equilibrium point within the game $G(\mathbf{q}_s)$.

We rely on the following proposition, applicable to concave games [40]: In the case where a concave game fulfills the dominance solvability condition:

$$-\frac{\partial^2 U_i}{\partial p_{s_i}^2} - \sum_{j=1, j\neq i}^{N} \left| \frac{\partial^2 U_i}{\partial p_{s_i} \partial p_{s_j}} \right| \geq 0 \tag{18}$$

the game $G(\mathbf{q}_s)$ admits a unique Nash equilibrium.

The mixed partial is written as:

$$\begin{aligned} \frac{\partial^2 U_i}{\partial p_{s_i} \partial p_{s_j}} &= \alpha_i^j \sum_{l=1}^{L_i} (1 + \chi_{il} k_{il}) \\ &+ \sum_{l=1}^{L_i} \phi_l \left[\frac{2\alpha_i^i \alpha_i^j B_{il}^2 M_{il}^2 \overline{v}_{il}^2 k_{il}^2 (1 + \chi_{il} k_{il})^2 \phi_l^2}{\left(B_{il} M_{il} + \sum\limits_{l=1}^{L_i} (1 + \chi_{il} k_{il}) \phi_l D_i \overline{v}_{il} \right)^3} \right] \geq 0 \end{aligned} \tag{19}$$

Then,

$$\begin{aligned} &-\frac{\partial^2 U_i}{\partial p_{s_i}^2} - \sum_{j=1, j\neq i}^{N} \left| \frac{\partial^2 U_i}{\partial p_{s_i} \partial p_{s_j}} \right| = (2\alpha_i^i - \sum_{j=1, j\neq i}^{N} \alpha_i^j) \\ &\times \sum_{l=1}^{L_i} (1 + \chi_{il} k_{il}) + (\alpha_i^i - \sum_{j=1, j\neq i}^{N} \alpha_i^j) \\ &\times \sum_{l=1}^{L_i} \phi_l \left[\frac{2(\alpha_i^i) B_{il}^2 M_{il}^2 \overline{v}_{il}^2 k_{il}^2 (1 + \chi_{il} k_{il})^2 \phi_l^2}{\left(B_{il} M_{il} + \sum\limits_{l=1}^{L_i} (1 + \chi_{il} k_{il}) \phi_l D_i \overline{v}_{il} \right)^3} \right] \geq 0 \end{aligned} \tag{20}$$

Thus, the game $G(\mathbf{q}_s)$ admits a unique Nash equilibrium. □

B. QoS game

The game G in QoS is defined for fixed $\mathbf{p}_s \in \mathscr{P}_s$ as $G(\mathbf{p}_s) = [\mathscr{N}, \{\mathscr{Q}_{s_i}\}, \{U_i(\mathbf{p}_s, .)\}]$.

Definition 2 *A QoS vector $\mathbf{q}_s^* = (q_{s_1}^*, ..., q_{s_N}^*)$ is a Nash equilibrium of the game $G(\mathbf{p}_s)$ if:*

$$\forall (i, q_{s_i}) \in (\mathscr{N}, \mathscr{Q}_{s_i}), U_i(\mathbf{p}_s, q_{s_i}^*, \mathbf{q}_{s_{-i}}^*) \geq U_i(\mathbf{p}_s, q_{s_i}, \mathbf{q}_{s_{-i}}^*)$$

Theorem 2 *For each $\mathbf{p}_s \in \mathscr{P}_s$, the game $[\mathscr{N}, \{\mathscr{Q}_{s_i}\}, \{U_i(\mathbf{p}_s, .)\}]$ admit a unique Nash Equilibrium.*

The second order derivative of the utility with respect to the prices is :

$$\frac{\partial^2 U_i}{\partial q_{s_i}^2} = -2\gamma_i (L_i - \sum_{l=1}^{L_i} k_{il}) \leq 0 \tag{21}$$

The second derivative is negative, it signifies the concavity of U_i and, consequently, assures the existence of a Nash equilibrium point within the game $G(\mathbf{p})$.

To demonstrate uniqueness, we adopt the approach outlined in [39] and establish the weighted sum of utility:

$$\vartheta\left(q_{s_k}, x\right) = \left[x_1 \nabla U_1\left(q_{s_1}, q_{s_{-1}}\right), ..., x_N \nabla U_N\left(q_{s_N}, q_{s_{-N}}\right)\right]^T \tag{22}$$

The pseudo-gradient of (22) is

$$\Xi\left(q_s, x\right) = \sum_{i=1}^{N} x_i U_i\left(q_{s_i}, q_{s_{-i}}\right) \tag{23}$$

The Jacobian matrix J of the pseudo-gradient (23) is

$$\mathbb{J} = \begin{bmatrix} x_1 \frac{\partial^2 U_1}{\partial q_{s_1}^2} & x_1 \frac{\partial^2 U_1}{\partial q_{s_1} \partial q_{s_2}} & \cdots & x_1 \frac{\partial^2 U_1}{\partial q_{s_1} \partial q_{s_N}} \\ x_2 \frac{\partial^2 U_2}{\partial q_{s_2} \partial q_{s_1}} & x_2 \frac{\partial^2 U_2}{\partial q_{s_2}^2} & \cdots & x_2 \frac{\partial^2 U_2}{\partial q_{s_2} \partial q_{s_N}} \\ \vdots & \vdots & \ddots & \vdots \\ x_N \frac{\partial^2 U_N}{\partial q_{s_1} \partial q_{s_2}} & x_N \frac{\partial^2 U_N}{\partial q_{s_N} \partial q_{s_2}} & \cdots & x_N \frac{\partial^2 U_N}{\partial q_{s_N}^2} \end{bmatrix} \tag{24}$$

Then

$$\mathbb{J} = \begin{bmatrix} -2r_1 & 0 & \cdots & 0 \\ 0 & -2r_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & -2r_N \end{bmatrix} \tag{25}$$

where $r_i = \gamma_i(L_i - \sum_{l=1}^{L_i} k_{il})$.

We have J is negative definite and according to [39], the functions $\psi(q_s, x)$ is diagonally strictly concave. Consequently, the uniqueness of the Nash equilibrium point is established. □

C. Learning Nash equilibrium

The best response algorithm, as outlined in [41], operates through a series of rounds. In each round, starting from the second onwards, each ISPs observes the prices (resp QoS) selected by its adversaries in prior rounds. Subsequently, the ISP incorporates these observed prices into its decision-making process to adjust its own price. Algorithm 1 provides a concise summary of the steps involved in the best response learning, guiding each ISPs towards finding the Nash equilibrium.

Algorithm 1 Best response Algorithm

1: Initialize vectors $\rho(0) = [\rho_1(0), ..., \rho_N(0)]$ randomly;
2: **For each** ISP_i at time instant t computes:
- $\rho_i(t+1) = \underset{\rho_i \in \mathscr{W}_i}{\text{argmax}} \left(U_i(\rho_i(t))\right)$.

3: **If** $\forall i \in \mathcal{N}$, $|\rho_i(t+1) - \rho_i(t)| < \epsilon$, then STOP.
4: **Else**, $t \leftarrow t+1$ and go to step (2).

Such as:

- ρ denotes the vector price $\mathbf{p}_s = (p_{s_1}, ..., p_{s_N})$ or vector QoS $\mathbf{q}_s = (q_{s_1}, ..., q_{s_N})$.
- $\mathscr{W}_i$ denotes the policy profile price $\mathscr{P}_{s_i}$ or policy profile QoS $\mathscr{Q}_{s_i}$.

V. NUMERICAL ILLUSTRATION

In this section, we shift our focus towards leveraging our analytical insights. Our strategy involves conducting a numerical analysis of the gaming market, incorporating the previously identified utility functions of the ISPs. To demonstrate, we consider a network scenario that includes three ISPs aiming to maximize their profits. Tables II and III present the system parameter values and environment parameter settings considered in this numerical study.

TABLE II
PARAMETERS SETTING USED FOR NUMERICAL EXAMPLES.

$\alpha_1^1 = \alpha_2^2 = \alpha_3^3$	$\alpha_i^j,\ i \neq j$	$\beta_1^1 = \beta_2^2 = \beta_3^3$	β_i^j
0.7	0.3	0.7	0.3
$\overline{p}_{s_1} = \overline{p}_{s_2} = \overline{p}_{s_3}$	$\underline{p}_{s_1} = \underline{p}_{s_2} = \underline{p}_{s_3}$	$L_1 = L_2 = L_3$	d_1
1000	1	35	200
$\overline{q}_{s_1} = \overline{q}_{s_2} = \overline{q}_{s_3}$	$\underline{q}_{s_1} = \underline{q}_{s_2} = \underline{q}_{s_3}$	$M_1 = M_2 = M_3$	d_2
1000	1	18	250
$B_1 = B_2 = B_3$	$\overline{v}_1 = \overline{v}_2 = \overline{v}_3$	$\gamma_1 = \gamma_2 = \gamma_3$	d_3
1000	300	5	300
$C_1 = C_2 = C_3$	$pt_1 = pt_2 = pt_3$	$\chi_1 = \chi_2 = \chi_3$	η
8	10	4	0.8
$p_{s_1} = p_{s_2} = p_{s_3}$	$q_{s_1} = q_{s_2} = q_{s_3}$	N	
300	250	3	

TABLE III
ENVIRONMENT PARAMETER SETTINGS.

Configuration	Parameters
Operating System	Windows 10 Pro 64-bit
Processor	Intel(R) Core(TM) i5-6300U CPU @ 2.40GHz, 4 cores
Memory	12 GB
Software	MATLAB R2020b.

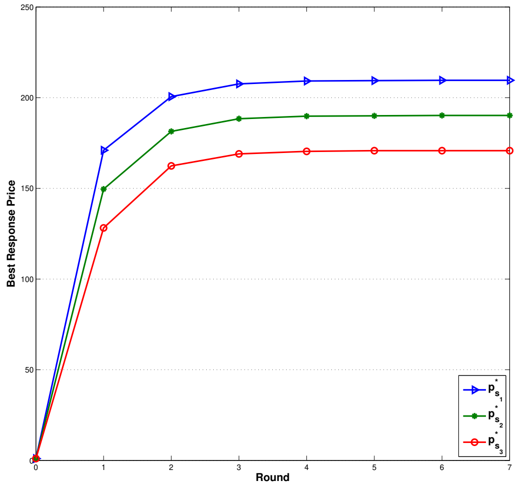

Fig. 2. Achieving price at the Nash equilibrium point.

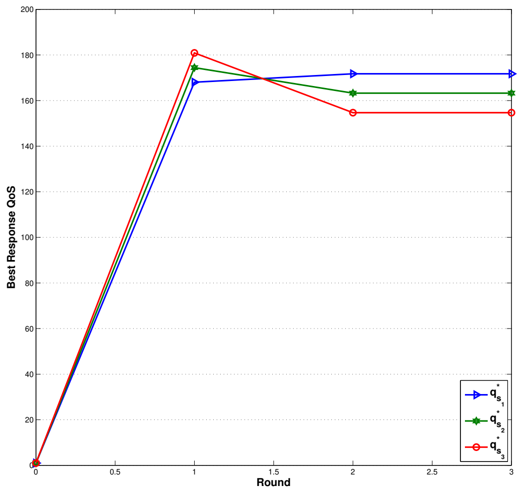

Fig. 3. Achieving QoS at the Nash equilibrium point.

Figures 2 and 3 illustrate the swift convergence towards Nash equilibrium in terms of price and QoS. The rapid convergence indicated by the low number of iterations required highlights the efficiency of the system in stabilizing. This swift adjustment suggests that ISPs quickly adapt their strategies to reach a stable point where no single ISP can benefit by unilaterally changing its strategy. Moreover, the presence and uniqueness of the Nash equilibrium point confirm that the system settles at a stable state where all ISPs' strategies are mutually optimal. This stability is crucial for predicting long-term outcomes and for strategic decision-making in competitive scenarios.

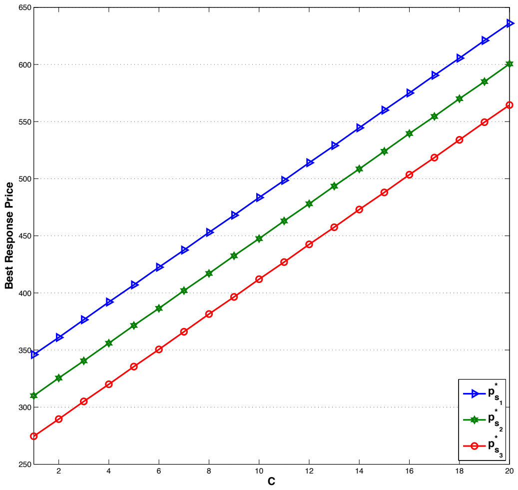

Fig. 4. Equilibrium price as a function of the caching cost.

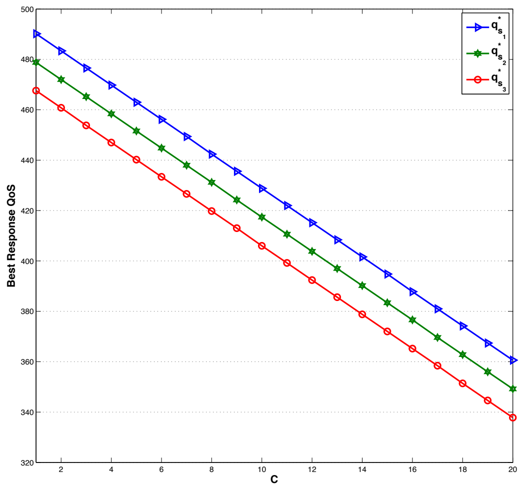

Fig. 5. Equilibrium QoS as a function of the caching cost.

Figures 4 and 5 provide insights into how Nash equilibrium price and QoS are influenced by rising caching costs for two ISPs. As the cost of caching content increases, ISPs tend to raise their prices while simultaneously reducing QoS. This trend arises because the higher expenses associated with caching make it less financially viable for ISPs to maintain extensive caching. Consequently, ISPs are compelled to forward more content requests to CP, which leads to higher transmission fees and greater backhaul bandwidth costs. To offset these increased costs, ISPs increase their prices. Moreover, to manage the additional burden of backhaul bandwidth expenses, ISPs lower the QoS they offer. These results underscore the financial strain that increased caching costs impose on ISPs, driving them to adjust their pricing strategies and QoS in response. The figures highlight the delicate balance ISPs must maintain between caching costs, pricing, and QoS to manage operational expenses and remain competitive.

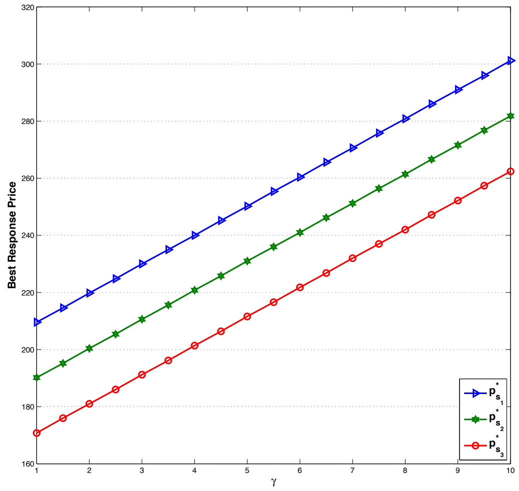

Fig. 6. Equilibrium price as a function of the bandwidth cost.

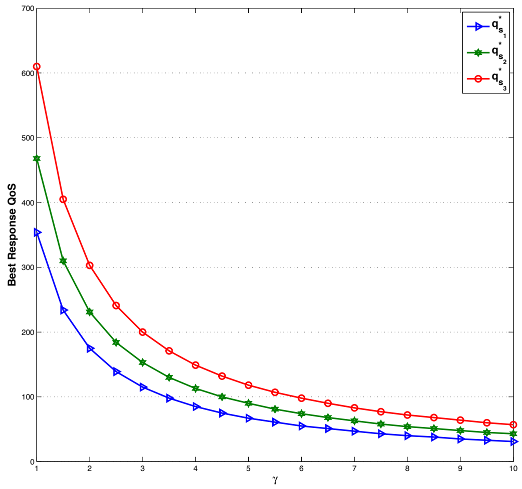

Fig. 7. Equilibrium QoS as a function of the bandwidth cost.

In Figures 6 and 7, we present the impact of bandwidth cost on price and QoS at Nash equilibrium. It is observed that the equilibrium price for both ISPs increases in response to higher bandwidth costs. Conversely, the equilibrium QoS for all ISPs decreases as the bandwidth cost rises. When the network owner sets a lower cost for bandwidth, ISPs tend to invest in more bandwidth to offer improved QoS and competitive pricing. However, as bandwidth costs escalate, ISPs opt to elevate their prices and reduce QoS to offset the increased cost of bandwidth.

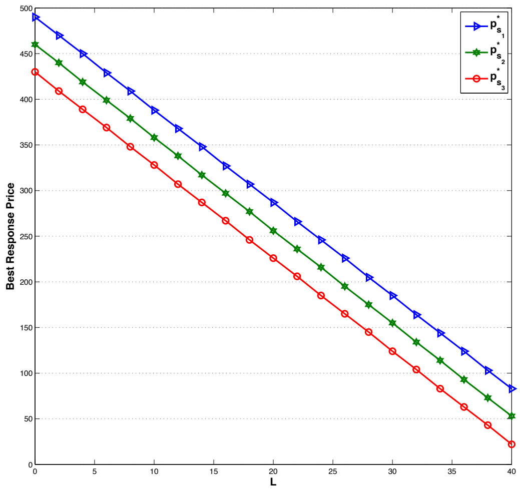

Fig. 8. Equilibrium price as a function of the number of cached items.

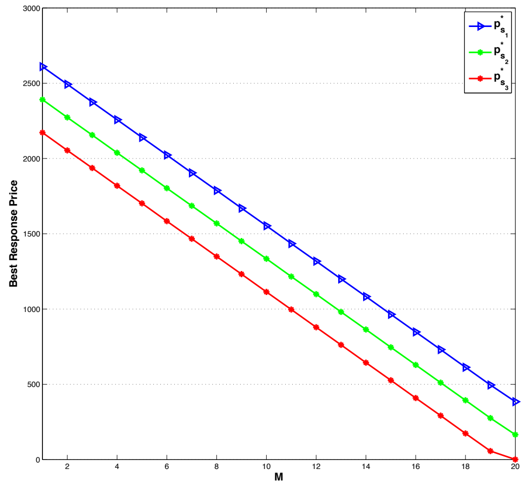

Fig. 10. Equilibrium price as a function of the quantity of advertisers.

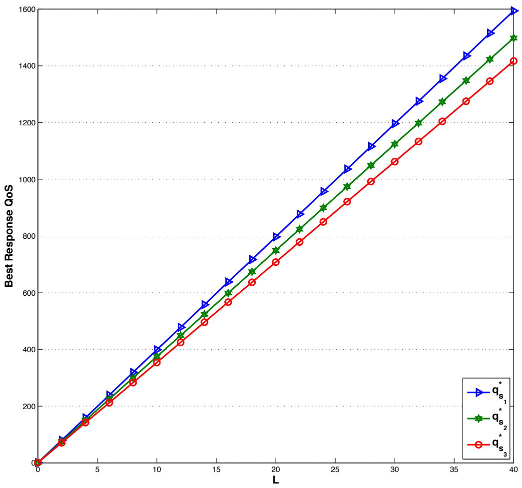

Fig. 9. Equilibrium QoS as a function of the number of cached items.

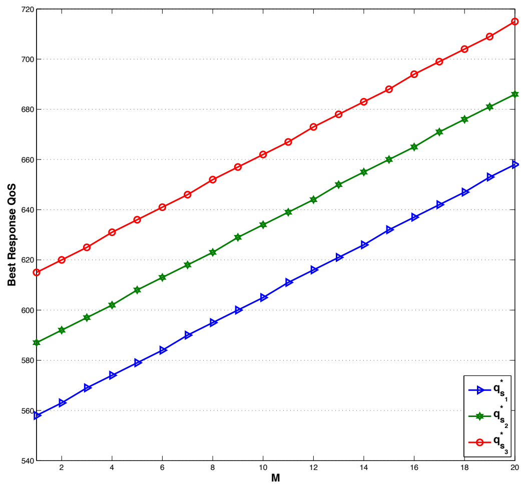

Fig. 11. Equilibrium QoS as a function of the quantity of advertisers.

Figures 8 and 9 reveal a significant relationship between the number of cached items, network access price, and QoS. As the number of items cached by ISPs increases, both the network access price and QoS improve. This is because a larger cache allows a greater proportion of content requests to be fulfilled directly from the ISP's cache, leading to lower transmission fees and reduced bandwidth costs. With these cost reductions, ISPs see an increase in revenue, which enables them to lower their access prices. The lower prices, in turn, attract more users, further boosting demand. Additionally, the enhanced QoS resulting from a larger cache improves user satisfaction and engagement. These findings underscore how increasing the cache size can create a positive feedback loop: it reduces costs, allows for lower pricing, improves QoS, and ultimately drives greater user demand and revenue for ISPs.

Figures 10 and 11 illustrate the impact of the number of advertisers on QoS and pricing for ISPs. As the number of advertisers increases, both QoS improves and prices decrease. This trend occurs because a higher number of advertisers generates more advertising revenue for the ISPs. With increased income from ads, ISPs are able to invest more in enhancing their QoS, leading to better QoS for users. Additionally, the increased revenue enables ISPs to lower their prices, making their services more attractive to users. This relationship aligns with real-world scenarios where greater advertising revenue provides ISPs with the financial flexibility to improve QoS and adjust pricing strategies to boost user demand and competitiveness.

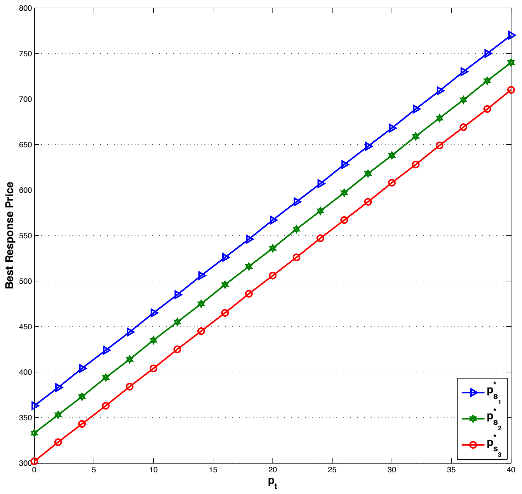

Fig. 12. Equilibrium price as a function of the transmission price.

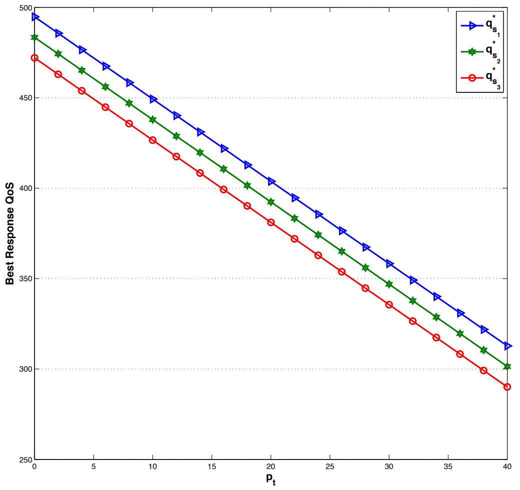

Fig. 13. Equilibrium QoS as a function of the transmission price.

Figures 12 and 13 illustrate the impact of transmission price on both the pricing and QoS provided by three ISPs. The data show that as the transmission price rises, ISPs reduce their prices and improve QoS. This counterintuitive outcome occurs because higher transmission prices lead to increased revenue from transmission fees, which boosts the ISPs' overall income. With greater financial resources, ISPs can afford to lower their access prices, making their services more attractive to consumers. Simultaneously, they invest more in bandwidth and infrastructure to enhance QoS. This dual strategy aims to maximize user demand by providing better QoS at lower prices, demonstrating how revenue from transmission fees can be leveraged to benefit users and improve competitive positioning.

VI. Conclusion

In this paper, we established an analytical framework to study the distribution of accessible content within an ICN environment encompassing multiple ISPs and advertisers. The interactions among ISPs were examined through a non-cooperative game, where each ISP has control over the amount of free content cached in the network and can adjust its strategies, including network access price and QoS. We assumed that the popularity of content adheres to a generalized Zipf distribution. We rigorously proved the existence and uniqueness of the Nash equilibrium in a competitive ICN market. This finding is significant as it suggests that a stable solution, accompanied by suitable economic incentives for collaborative caching, is attainable within the ICN paradigm. Furthermore, we outlined a learning mechanism enabling each ISP to swiftly and accurately discover its equilibrium policies. Our simulation results underscored the benefits of caching investment for both ISPs and end-users, demonstrating the efficacy of our proposed approach in fostering mutually advantageous outcomes within the ICN ecosystem. Results from this work can be further extended to more general network scenarios, particularly when considering non-linear demand and when valuation follows a normal distribution.

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