Cooperative WiFi Tethering Control Algorithm Based on the Meta-Bargaining Approach

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ABSTRACT Exchange of resources and services over sharing economy networks is attracting increasing interest. In response to this trend, Internet of Things and sharing economy are two emerging paradigms to encourage people to share their assets, which could include personal devices with others. In this study, we propose a novel coordinated WiFi tethering algorithm for a number of mobile devices. Under the dynamic changing WiFi environment, the main issue is to effectively share the limited spectrum resource. To design our tethering algorithm, we adopt four different bargaining solutions, and introduce the meta-bargaining approach to handle comprehensively the spectrum resource. Therefore, we formulate network agents’ competitive interactions as a cooperative game model, and they can reach an agreement that gives mutual advantage while maximizing the system performance. To get a fair-efficient WiFi tethering performance, the main novelty of our proposed meta-bargaining approach is to ensure a relevant tradeoff among different bargaining solutions. Some simulation results and numerical analysis are provided to confirm the effectiveness of our proposed scheme. Specifically, according to our meta-bargaining approach, the device payoff, system throughput and fairness are improved by about 15%, 15% and 20%, respectively, in comparison with existing protocols.

INDEX TERMS WiFi tethering, Nash bargaining, proportional bargaining solutions, meta-bargaining approach, cooperative game model.

I. INTRODUCTION

The concept of the prominent Internet-of-Things (IoT) notion is envisioned to improve the quality of modern life. In recent years, IoT has found its application in multiple intelligence fields, such as connected-industry, smart-city, smart-home, self-driving car, intelligent-building and smart-campus, among other domains. This led to an unprecedented increase in the number of IoT devices that are deployed and operated around the world. According to the ‘Ericsson Mobility Report 2018’, the number of IoT devices is expected to exceed 4.1 billion in 2024, increasing at a compound annual growth rate of 33% since 2013. However, many IoT devices have severely limited computation and communication capacities. Hence, many computing tasks are offloaded for intensive processing. Under these circumstances, the fundamental control issue of IoT device operations is how to effectively use the limited system resource when massive concurrent access demands are requested [1], [2].

As an emerging economic-technological paradigm, sharing economy is a new economic trend that promotes a novel model of sharing resources and services. Over the last couple of years, sharing economy has been on an exponential growth curve and has been the subject of considerable interest across the globe. Usually, it refers to peer-based activities of sharing the access to goods and services. By leveraging idle resources to produce more profits, the sharing economy is coordinated through community-based online services. In contrast with traditional ownership-based models, sharing economy provides a collaborative consumption rather than having individual ownership. The success of sharing economy is best manifested by the fact that it encompasses very diverse models. The most promising model is the IoT based
WiFi tethering model, which means smart devices and digital services that help users share physical resources [3], [4]. Tethering technology is to share the Internet connection of a mobile IoT device, with other nearby devices. Typically, the mobile IoT device is connected to the Internet via wireless cellular networks or over WiFi networks. If tethering is done over WiFi, then the Internet-connected IoT device acts as a portable WiFi access point (AP), known as mobile AP, and relays data from/to Internet for nearby other IoT devices, called client devices. Client IoT devices do not have their direct connectivity to Internet; they connect to the corresponding mobile AP with their WiFi interfaces. With the WiFi tethering mechanism, end-users can go online from their WiFi-enabled devices even when no public APs are available. Due to its flexibility and affordability, the WiFi tethering technology can be a useful tool to implement the sharing economy while providing on-the-go mobile users’ Internet connection [5], [6].

In this study, we design a new WiFi tethering control algorithm with the goal of improving the overall system performance. By taking into account the load balancing among mobile APs, we develop a novel WiFi spectrum resource sharing mechanism. However, it is an extremely challenging and difficult work. Therefore, finding an intelligent control paradigm would be needed. To satisfy this goal, we adopt the basic idea of cooperative game theory. First, we exploit four different bargaining solutions; Nash bargaining solution (NBS), Kalai–Smorodinsky solution (KSS), egalitarian bargaining solution (EBS), and asymmetric Kalai–Smorodinsky solution (AKSS). By using the concepts of NBS, AKSS, KSS, and EBS, we implement our meta-cooperative game model to reason about how to produce a desired outcome. All of our approach is a subfield of game theory. Nowadays, game theory has been widely recognized as an important tool in many fields, and applies to a wide range of future networks and data communications [7], [8].

A. TECHNICAL CONCEPTS

In the WiFi tethering management algorithm, autonomous, distributed, and intelligent mobile APs independently make rational and strategic decisions. This scenario may fall into game theory. Therefore, we formulate our WiFi tethering control algorithm based on the bargaining game solutions. In 1950, J. Nash introduced the idea of NBS, and characterized it by axioms. The NBS consists of each player’s status quo payoff in addition to a share of the benefits occurring from cooperation; it is a unique and fair-efficient solution. However, one of the criticisms of NBS is precisely that it is not fair, in the sense that it ignores the players’ ideal payoffs. To get around this drawback, several proportional bargaining solutions have been provided - those of KSS, EBS and AKSS, arguably being the most influential. Especially, the KSS and EBS can be pinned down by axioms that are well known when it comes to characterizing the NBS. As one of asymmetric solutions, the AKSS is an extension of the classical KSS; it is characterized by the inter-player weight based on both egalitarian and utilitarian principles [7], [8].

When game players face a bargaining problem, they can come up with different solution concepts; different notions of fairness and equity. To reach an unanimous consensus, E. Damme introduced the meta-bargaining model. Its purpose is to clarify what could be a reasonable bargaining solution if players have different ideas about the ideal solution concept to be applied. Usually, meta bargaining game is a non-cooperative game in a strategic form generated by given cooperative bargaining process. Therefore, it is characterized by the fact that the players’ strategy set is a set of bargaining solutions. In this paper, we develop a new meta bargaining model. In contrast to the Damme’s meta game, our proposed meta bargaining approach is universal in the sense that all different bargaining solutions are allowed as strategic choices. Therefore, our game outcome can hold different bargaining solutions’ features for any game players [9].

B. MAIN CONTRIBUTIONS

In the WiFi tethering platform, mobile APs share their spectrum resources according to a cooperative-competitive manner. In the current traffic situation, each individual mobile AP has a different viewpoint for the effectual WiFi spectrum allocation. To reach a mutually acceptable agreement, the concept of meta-bargaining approach is applied. With the combination of NBS, AKSS, KSS, and EBS, we can leverage the full synergy of different bargaining solutions to effectively allocate the limited spectrum resource. In detail, the major contributions of this study are as follows:

- This study considers the spectrum allocation problem in the WiFi tethering infrastructure. During the interactive meta bargaining process, the limited spectrum resource is fair-efficiently distributed to multiple mobile APs.
- We adopt the NBS, AKSS, KSS, and EBS bargaining solutions to comprehensively handle the WiFi tethering circumstance at the decision time. Each bargaining solution has different characteristics and features for the bargaining problems. Based on these four different bargaining solutions, individual mobile APs can estimate their assigned spectrum amounts.
- To share the limited WiFi spectrum resource, we clarify what could be a reasonable solution among mobile APs if they have different ideas about the ideal bargaining solution. To get a reciprocal consensus, we put different weighting factors for the NBS, AKSS, KSS, and EBS by considering the current network conditions.
- The main characteristic of our meta-bargaining approach lies in its responsiveness to the reciprocal combination of NBS, AKSS, KSS, and EBS. For the WiFi spectrum sharing problem, each independent mobile AP agrees on the final outcome in a cooperative manner.
- We perform numerical studies to evaluate the performances of our proposed scheme, and make a series of comparisons with the existing state-of-the-art protocols.
Finally, we conduct computer simulations and discuss numerical results to verify the superiority of our meta-bargaining approach.

C. ORGANIZATION

We organize the rest of paper as follows. After giving a literature overview that covers the related work in section II, we present the WiFi tethering platform and formulate the WiFi spectrum sharing problem in Section III. And then, we introduce the basic ideas of NBS, AKSS, KSS, and EBS to design our WiFi spectrum allocation scheme. Based on the meta-bargaining approach, the main steps of our proposed algorithm are given to increase readability. Section IV provides simulation results that validate the performance and effectiveness of the proposed algorithm. Finally, Section V concludes the paper.

II. RELATED WORK

There exist some research efforts with respect to the spectrum efficiency in the WiFi tethering platform. This section presents prior efforts related to the tethering control issue.

The paper [6] proposes the Coordinated Tethering over White Spaces (CTWS) scheme for operator-controlled tethering operations. White space is a radio frequency range, which is created when there are gaps between television channels. These space can provide broadband internet access that is similar to that of 4G mobile. The CTWS scheme does not add to the existing infrastructure but instead allows the individual IoT devices to act as mobile APs and to tether data to and from other client devices. This approach iteratively clusters the client devices into mobile APs, and allocates the spectrum resources to maximize the system efficiency. Therefore, it allows more efficient resource distribution among users in dense areas. Main contribution of the CTWS scheme is to meet device demands with low cost by configuring the WiFi tethering platform [6].

The Relationship based Resource Sharing Management (RRSM) scheme is a protocol that uses online social relationships to meet devices’ demands for the system resource management [10]. Based on the online social relationship between IoT devices, this scheme automatically determines how much resources the mobile device is allowed to use. The RRSM scheme enables mobile devices to reduce their costs of device sharing with other devices according to the social closeness. When a mobile AP receives a tethering connection request from a client device, the mobile AP first sends a request to the authentication server. Then, the authentication server evaluates the social relationship and determines how much of the resource on the mobile AP can be used by a client device. Through the simulation analysis, this approach can effectively limit the resource usage for client devices while enabling altruistic device to share the resource [10].

M. Zhang et al. propose the Mobile Collaborative Internet Access (MCIA) scheme. This scheme models the relationship of multiple mobile APs and client devices where mobile devices share their Internet access through mobile APs [11]. In the MCIA scheme, mobile APs choose pricing policies, and client devices select a dedicated mobile AP. Hence, this protocol formulates the interaction between mobile APs and client devices as a two-stage Stackelberg game model. In Stage I, the mobile APs determine the access and tethering prices; they decide their hybrid prices in a cooperative manner jointly to maximize their total profit. In Stage II, the neighboring client devices coordinate to decide the amount of traffic to download and to tether to maximize their total payoff. The analysis of equilibria lies in the multiple ways in which the devices can configure their access connections, either through direct access or tethering to another device [11].

All the earlier work has attracted a lot of attention and introduced unique challenges. Different from existing CTWS, RRSM and MCIA protocols, our meta-bargaining approach can obtain a rational consensus for the effective WiFi tethering operation. Therefore, mobile APs share their spectrum resources according to a cooperative-competitive manner.

III. META-BARGAINING APPROACH FOR THE WiFi TETHERING

A. WiFi TETHERING SYSTEM ARCHITECTURE

In typical wireless communication environments, the most common method for mobile devices to get access to the Internet is for each of them to use 4G/5G connections separately without cooperation. Recently, most mobile devices have at least two network interfaces: one is for the cellular network and the other is for the WiFi access. Cellular network communications consume significantly more power than the WiFi access. However, in WiFi communications, some mobile devices can be far away from the public AP to get the WiFi access. In this case, the overall power consumption for the whole group of mobile devices can be reduced by selecting a certain number of devices to take mobile AP roles while the other mobile devices get Internet access through WiFi by using mobile APs [12].

In this study, we consider a small WiFi tethering platform based on the WiFi cooperation topology, which comprises two types of mobile devices with the WiFi spectrum resource pool (χ); χ can be assigned with an approximately interference-free spectrum bands. There are a set $\mathcal{A} = \{A_1, \ldots, A_n\}$ of mobile APs and a set $\mathcal{M} = \{M_1, \ldots, M_m\}$ of client mobile devices. Simply, we assume each individual $M_i$ and $\mathcal{A}$ subscribes to only one $A_{i_1}, \ldots, A_{i_n}$, which provides a mobile Internet service for each of its subscribers. Let $\mathcal{M}_i$ and $R_{\mathcal{A}_i}$ denote the set of subscribers of $A_i$ and the allocated spectrum resource of $A_i$, respectively, where $\bigcup_{A_i \in \mathcal{A}} R_{A_i} = \chi$. Each $\mathcal{M}_i$ generates application tasks. Usually, these tasks can be categorized into two classes: class I (real-time data) tasks and class II (non-real-time data) tasks. Class I data traffic is highly delay sensitive, but class II data traffic is rather tolerant of delays. $\mathcal{R}_{M_i}$ is the spectrum request of $\mathcal{M}_i$’s tasks. All $\mathcal{A}$ and $\mathcal{M}$ remain relatively still, e.g., as students in a lecture hall. $\chi$ is the total WiFi spectrum resource pool, and it is orthogonally assigned to multiple $A$ s in a
cooperative manner. Traditionally, the WiFi tethering system is considered in a centralized way; a centralized controller needs to collect the control information by methods like extending IEEE 802.11 protocol. The detailed protocol extension and practical deployment are out of the scope of this study [11], [12].

In this study, we consider the constant spectrum resource constraint of each $M_i$, since this is the main restriction in practical cellular traffic. To effectively distribute the $\chi$ among $A_i$ in $A$, a modeling situation is formulated as a meta-bargaining game ($\mathcal{G}$). In the $\mathcal{G}$, game players are $A_{1 \leq i \leq N} \in A$ and the assigned WiFi spectrum resources, i.e., $R_{Ai}$, are their strategies where $\chi \geq \sum_{A_i \in A} R_{Ai}$. Based on the $R_{Ai}$, the $A_i$’s utility function ($U_{Ai} (\cdot)$) is defined as follows:

$$U_{Ai} (R_{Ai}, S_{Ai}, r_{Ai}) = \mathbb{1}_{Ai} - (R_{Ai} \times r_{Ai})$$

s.t.,

$$S_{Ai} = \sum_{M_j \in M_{Ai}} R_{Mj}$$

(1)

where $\kappa$, $\eta$ and $\xi$ are coefficient factors for the $U_{Ai} (\cdot)$. $r_{Ai}$ is the price per bit for the WiFi tethering service. According to $U_{Ai} (\cdot)$, how to decide the amount of $R_{Ai}$ for each $A_i$ is the main challenge in this study.

B. THE BASIC CONCEPTS OF DIFFERENT BARGAINING SOLUTIONS

Almost seventy years ago, J. Nash published his seminal paper on what is now known as the axiomatic bargaining solution. In the bargaining solution, game players have access to any of the alternatives in some feasible set. If they reach a compromise on a particular alternative, that is what they get. The goal of bargaining solution is to predict how game players would settle their differences, or how an impartial arbitrator would identify a fair compromise to recommend to them [13]. In 1975, Kalai and Smorodinsky noted that Nash bargaining solution failed to satisfy certain properties they felt were desirable. Consequently, they characterized new bargaining solutions. In these solutions, they equalize the ratios between the players’ payoffs and their ideal payoffs, which are the maximal possible payoffs the players can achieve if everyone else receives their minimal acceptable payoffs. Based on the relative ratios, AKSS, KSS, and EBS are correlative defined as the family of proportional bargaining solutions [14].

To explain bargaining solutions, we introduce the notation and basic definitions, which are used throughout this paper.

Let $N = \{1, \ldots, n\}$ be a finite set of game players. $\mathbb{R}$ and $\mathbb{R}^N$ are the set of all real numbers, and the $n$-fold Cartesian product of $\mathbb{R}$, respectively. A bargaining problem is a pair $(S, d)$ where $S \subseteq \mathbb{R}^N$ is a set of feasible utility allocations, and $d \in S$ is a disagreement point. The interpretation of a problem $(S, d)$ is that the $n$ players need to agree on a single allocation in $S$ where there is $s \in S$ with $s > d$. If they agree on $s$ then each player $i$ obtains the utility payoff $s_i$. Otherwise, every players receive their respective disagreement value $d_i$. The player $i$’s ideal payoff is $a_i (S, d) = \max \left\{ s_i : s \in S, s_j \geq d_j \text{ forall } j \neq i \right\}$. Typically, this point is not feasible where $a_i (S, d) = (a_1 (S, d), \ldots, a_n (S, d)) \notin S$. A bargaining solution is a map $\mathcal{P}$, that assigns to every problem $(S, d)$ a unique feasible point $\mathcal{P}(S, d) \in S$. Different bargaining solutions are characterized with certain properties [7].

A crucial issue of bargaining solutions is how the individual payoffs compare to each other. The NBS maps any problem $S$ to the unique point in $S$; it is mathematically defined as follows [7]:

$$\mathcal{P}^{NBS} (S) = \max \prod_{i \in N} (x_i - d_i)$$

(2)

where $x = [x_1, \ldots, x_i, \ldots, x_n]$ is a vector and $x \in S$. Usually, the NBS is a prime example of bargaining problems. Since the early 1970s, from another angle, the focus has shifted to the dependence of proportional solutions with ideal points. With a non-negative number $\rho$, the EBS, AKSS and KSS and is defined as follows [7]:

$$\begin{cases} \mathcal{P}^{EBS}_i (S) / \mathcal{P}^{EBS}_i (S) = \left( a_i (S) / a_i (S) \right)^{\rho=0} \\ \mathcal{P}^{AKSS}_i (S) / \mathcal{P}^{AKSS}_i (S) = \left( a_i (S) / a_i (S) \right)^{0<\rho<1} \\ \mathcal{P}^{KSS}_i (S) / \mathcal{P}^{KSS}_i (S) = \left( a_i (S) / a_i (S) \right)^{\rho=1} \end{cases}$$

s.t., $i, j \in N$

(3)

For instance, the EBS equalizes the payoffs and the KSS equalizes the fractions of the ideal payoffs that players achieve; that is, \( \mathcal{P}^{EBS}_i (S) / \mathcal{P}^{EBS}_i (S) = 1 \) and \( \mathcal{P}^{KSS}_i (S) / \mathcal{P}^{KSS}_i (S) = (a_i (S) / a_i (S)) \), respectively, in $S$. More generally, EBS and KSS belong to the following class of bargaining solutions given by $0 \leq \rho \leq 1$. The AKSS for any problem $S$ can be expressed as $\lambda \cdot (a_1 (S)^\rho \ldots a_n (S)^\rho)$ where $\lambda$ is the maximum possible. In general, the parameter $\rho$ measures the advantage of having a large ideal payoff. There is no advantage for the EBS, and as $\rho$ increases this advantage increases as well [7].

Usually, bargaining solutions are characterized by a collection of desirable axioms like as, Anonymity (A), Individual Monotonicity (IM), Strong Individual Rationality (SIR), Homogeneity (H), Homogeneous Ideal Independence of Irrelevant Alternatives (HIHIA), Midpoint domination (MD), Independence of Irrelevant Alternatives (IIA) and
Pairwise Ratio Independence (PRI) and Disagreement Convexity (DC). The axioms involved in the characterization of NBS are A, SIR, H, HIIIA, IIA and PRI. The EBS, AKSS and KSS commonly satisfy the axioms of A, SIR, H, HIIIA, IM and PRI. Supplementarily, the KSS may satisfy the MD axiom, and the EBS may satisfy the IIA and DC axioms [7].

- **A**: For a permutation \( \pi : N \rightarrow N \) and a problem \( S \), we write \( \pi(S) = \{ (s_1, \cdots, s_{\pi(n)}) : s \in S \} \). \( \mathfrak{P}_{\pi(i)}(S) = \mathfrak{P}_i(\pi(S)) \) for all \( i \in N \), all problems \( S \) and all permutations \( \pi \).
- **IM**: \( \mathfrak{P}_i(S) \leq \mathfrak{P}_j(T) \) for all \( i \in N \) and all problems \( S, T \) with \( S \subseteq T \), \( a_i(S) \leq a_j(T) \), and \( a_i(S) = a_j(T) \) for all \( j \neq i \).
- **SIR**: \( \mathfrak{P}(S) > 0 \) for all problems \( S \).
- **H**: \( \mathfrak{P}(\lambda \cdot S) = \lambda \cdot \mathfrak{P}(S) \) for all problems \( S \) and all \( \lambda \in \mathbb{R}_+ \).
- **HIIIA**: \( \mathfrak{P}(S) = \mathfrak{P}(T) \) for all bargaining problems \( S, T \) with \( S \subseteq T \), \( \mathfrak{P}(T) \in S \), and \( a(S) = r \cdot a(T) \) for some \( r \leq 1 \).
- **MD**: \( \mathfrak{P}(S) \geq n^{-1} \cdot a(S) \) for all bargaining problems \( S \).
- **IIA**: \( \mathfrak{P}(\lambda \cdot S) = \lambda \cdot \mathfrak{P}(S) \) for all bargaining problems \( S \) with \( S \subseteq T \) and \( \mathfrak{P}(T) \in S \).
- **PRI**: For two vectors \( k, x \in \mathbb{R}_n^+ \), we define \( k \circ x = (k_1 \cdot x_1), \cdots, k_n \cdot x_n \). \( \mathfrak{P}(k \circ S) \mathfrak{P}(k \circ T) = \frac{\mathfrak{P}(S)}{\mathfrak{P}(T)}(\mathfrak{P}(S)) \) for all problems \( S \) with \( \mathfrak{P}(S) > 0 \) and all \( k \in \mathbb{R}_+^n \) with \( k_i = k_j \).
- **DC**: \( \mathfrak{P}(S, (\lambda \cdot d + (1 - \lambda) \cdot \mathfrak{P}(S, d))) = \mathfrak{P}(S, d) \) for all bargaining problems \( S, d \) and all \( \lambda \in (0, 1] \).

C. THE META-BARGAINING CONTROL SCHEME FOR WiFi TETHERING

In this study, we design a new spectrum allocation scheme for the WiFi tethering platform. The major goal of our scheme is to adaptively allocate the limited spectrum resource to multiple BSs based on the meta-bargaining model. To reduce computation complexity, the spectrum allocation process is specified in terms of basic spectrum units (BSUs), where one BSU is the minimum amount (e.g., 512 Kb in our system) of spectrum allocation. Each individual \( A \) has its own \( S_A \), and shares the \( \chi \) with other \( A \)s. To implement the spectrum allocation process, our proposed scheme consists of two phases. At the first phase, we obtain the NBS, EBS, AKSS and KSS for all \( A \)s, independently. To get them, let \( U_A = [U_{A_1}, \ldots, U_{A_n}] \subseteq \mathbb{R}^k \) be a set of feasible utility payoffs, and \( d_A = [d_{A_1}, \ldots, d_{A_n}] \) is the disagree point vector for each \( A \). Mathematically, the NBS for the bargaining problem \((U_A, d_A)\), i.e., \( \mathfrak{P}^{\text{NBS}}_A(U_A, d_A) \), is given by:

\[
\mathfrak{P}^{\text{NBS}}_A(U_A, d_A) = \max \prod_{A_i \in A} \left( U_{A_i} \left( R_{A_i}, S_{A_i}, r_{A_i} \right) - d_{A_i} \right) \quad \text{s.t. } \chi = \sum_{A_i \in A} S_{A_i} \quad (4)
\]

The EBS for \((U_A, d_A)\), i.e., \( \mathfrak{P}^{\text{EBS}}_A(U_A, d_A) \), is given by:

\[
\mathfrak{P}^{\text{EBS}}_A(U_A, d_A)
\]

\[
= \left[ U_{A_i} \left( R_{A_i}, S_{A_i}, r_{A_i} \right) - d_{A_i} \right] \quad (5)
\]

To calculate the AKSS for \((U_A, d_A)\), i.e., \( \mathfrak{P}^{\text{AKSS}}_A(U_A, d_A) \), we should define the power parameters, i.e., \( \rho = [\rho_1 \ldots \rho_n] \).

In our proposed scheme, the values of \( \rho_1 \leq \rho_n \) are decided according to the user’s quality of experience (QoE). Traditionally, class I task services have a higher priority than class II task services. By considering the service QoE, the \( \rho_1 \leq \rho_n \) values are decided based on the ratio of class I data tasks to class II data tasks. For the \( A_i \), the power parameter \( \rho_i \) is given by:

\[
\rho_i = \gamma_{A_i} \sum_{A_i \in A} (\gamma_{A_i}) \quad \text{s.t. } \gamma_{A_i} = \frac{\Theta^I_{A_i}}{\Theta^I_{A_i} + \Theta^H_{A_i}} \quad (6)
\]

where \( \Theta^I_{A_i} \) and \( \Theta^H_{A_i} \) are the total requested spectrum sums of class I and class II tasks, respectively, from the \( A_i \). Using (6), the \( \mathfrak{P}^{\text{AKSS}}_A(U_A,d_A) \) is given by:

\[
\mathfrak{P}^{\text{AKSS}}_A(U_A,d_A)
\]

\[
= \left[ U_{A_i} \left( R_{A_i}, S_{A_i}, r_{A_i} \right) - d_{A_i} \right] \quad (7)
\]

Simply, the KSS for \((U_A, d_A)\), i.e., \( \mathfrak{P}^{\text{KSS}}_A(U_A,d_A) \), is obtained based on the \( \mathfrak{P}^{\text{AKSS}}_A(U_A,d_A) \) with \( \rho = 1 \), i.e., \( \rho_1 \leq \rho_n = 1 \).

At the second phase, we formulate the meta-bargaining model to get the final solution for the WiFi spectrum allocation. At the first phase, we can get the four different bargaining solutions. In the viewpoint of \( A_i \), the NBS, EBS, AKSS and KSS are \( \mathfrak{P}^{\text{NBS}}_A \), \( \mathfrak{P}^{\text{EBS}}_A \), \( \mathfrak{P}^{\text{AKSS}}_A \) and \( \mathfrak{P}^{\text{KSS}}_A \), respectively. According to this information, we re-negotiate the WiFi spectrum sharing problem, and determine the weighting factor for each bargaining solution. By considering the DC axiom, we can decide the weighting factor of \( \mathfrak{P}^{\text{EBS}}_A(U_A,d_A) \), i.e.,
\( P^{EBS} \), based on the load balancing idea,
\[
\Gamma^{EBS}_A = \beta \frac{\max_{A_i \in A} (S_{A_i}) - \min_{A_i \in A} (S_{A_i})}{\max_{A_i \in A} (S_{A_i})}
\]
(8)

where \( \beta \) is an adjustment constant for the \( \Gamma^{EBS}_A \). By considering the end user’s QoE, we may emphasize the class I traffic services. Therefore, we can decide the weighting factor of \( \Gamma^{AKSS}_A (U_A, d_A) \), i.e., \( \Gamma^{AKSS}_A \), based on the total class I task ratio,
\[
\Gamma^{AKSS}_A = \beta \frac{\Theta_{IIA}^I / (\Theta^{II}_T + \Theta^{III}_T)}{\Theta_{IIA}^I + \Theta^{III}_T} = \frac{1}{\beta} \Gamma^{AKSS}_A
\]
(9)

According to the reciprocal complement relationship between \( \Gamma^{AKSS}_A (U_A, d_A) \) and \( \Gamma^{EBS}_A (U_A, d_A) \), the weighting factor of \( \Gamma^{KSS}_A (U_A, d_A) \), i.e., \( \Gamma^{KSS}_A \), is simply given by;
\[
\Gamma^{KSS}_A = \beta \frac{\Theta_{IIA}^I / (\Theta^{II}_T + \Theta^{III}_T)}{\Theta_{IIA}^I + \Theta^{III}_T} = \frac{1}{\beta} \Gamma^{KSS}_A
\]
(10)

The prominent feature associated with \( NBS \) is the axiom II(A); it states that if the bargaining solution of the larger set is found on a smaller domain, then the solution is not affected by expanding the domain. Therefore, the II(A) axiom provides a powerful property for our WiFi spectrum allocation algorithm when there are utility limits for each user [15]. For example, if the class II task services are strongly concerned with their service reliability, it might be possible that in class II tasks, a higher QoE level is not required. For this reason, the weighting factor of \( \Gamma^{NBS}_A (U_A, d_A) \), i.e., \( \Gamma^{NBS}_A \), is decided as follows;
\[
\Gamma^{NBS}_A = (\Theta_{IIA}^I + \Theta^{III}_T) / (\Theta_{IIA}^I + \Theta^{III}_T)
\]
(11)

\[\text{s.t.} \Theta_{IIA}^I = \sum_{A_i \in A} \sum_{M_j \in M_{A_i}} m^{II}_j \]

where \( m^{II}_j \) is the minimum spectrum requirement for the class II services from the \( M_j \). According to (8)-(11), we can get the weighting factors for the NBS, EBS, AKSS and KSS, respectively, and formulate our meta game model to get the final solution for the WiFi spectrum sharing problem.

The main steps of the proposed scheme can be described as follows:

**Step 1:** For our simulation model, the values of system parameters and control factors can be discovered in Table 1, and the simulation scenario is given in Section IV.

**TABLE 1. System parameters used in the simulation experiments.**

| Parameter   | Value | Description                  |
|-------------|-------|------------------------------|
| \( n \)     | 4     | the number of mobile APs in the tethering system |
| \( m \)     | 40    | the number of client devices in the tethering system |
| \( \kappa \) | 2     | a coefficient factor for \( U_A(\cdot) \) |
| \( \chi \)  | 20 Giga bps | total spectrum capacity in the tethering system |
| \( \eta \)  | 1.5   | a coefficient factor for \( U_A(\cdot) \) |
| \( \xi \)   | 1     | a coefficient factor for \( U_A(\cdot) \) |
| \( \tau \)  | 3     | the price per bit for the WiFi tethering service |
| \( \beta \) | 1     | an adjustment constant for the \( \Gamma^{EBS}_A \) |

Based on the \( \Phi_A (\cdot) \), our proposed scheme calculates the final spectrum allocation amount for the \( A_i \), i.e., \( \psi_{A_i} \); it is estimated according to a social choice rule, which can be interpreted as a means to give a relative justification for the NBS, EBS, AKSS and KSS based on the current WiFi system situation. Finally, the \( \psi_{A_i} \) is given (13), as shown at the bottom of the page.
Step 2: In each network operation period, individual mobile devices (M) generate their task services, and contact their corresponding mobile APs (A). Individual M reports its spectrum request amount (RM) to its corresponding A.

Step 3: Based on the RM information, each individual A estimate its SA, which is a main parameter to calculate the A’s utility payoff.

Step 4: At the first phase, we get the four different bargaining solutions. According to (4),(5),(6), the NBS, EBS, AKSS are obtained, respectively. By using (6), the KSS is given with ρ = 1. Therefore, the P_A^(NBS) (UA, d_A), P_A^(EBS) (UA, d_A), P_A^(AKSS) (UA, d_A) and P_A^(KSS) (UA, d_A) are determined to share the limited χ resource.

Step 5: At the second phase, we re-negotiate the WiFi spectrum allocation solution based on the meta-bargaining game model. For the EBS, AKSS, KSS and NBS, we define the weighting factors by using (8)-(11). These decisions are made based on the current WiFi traffic conditions.

Step 6: In an adaptive online fashion, we get the meta-bargaining solution (ΦA (UA, d_A)) according to (12)-(13). Finally, the spectrum amount (ψA1≤i≤M) is assigned to each A1≤i≤M.

Step 7: In the WiFi tethering platform, multiple mobile APs collaborate with another in a coordinated manner to strike the appropriate performance balance while adaptively handling the current traffic situations.

Step 8: Constantly, the A’s and M’s are self-monitoring the current WiFi system conditions, and proceed to Step 2 for the next spectrum allocation process.

IV. PERFORMANCE EVALUATION
In this section, the performance of our proposed scheme is compared with other existing protocols through computer simulations.

A. EXPERIMENTAL METHOD
The assumptions of our simulation environments are as follows:
- The simulated WiFi tethering platform consists of 4 mobile APs (A’s) and 40 client mobile devices (M’s) where |A| = 4 and |M| = 40.
- Client mobile devices are distributed randomly over the WiFi tethering area.
- The process for service task generations is Poisson with rate λ (services/s), and the range of offered service load was varied from 0 to 3.0.
- Six different kinds of application tasks are assumed based on connection duration and spectrum requirement. In each mobile device, applications are generated randomly.
- Among the generated different kinds of applications, some applications need class I data services, and others need class II data services. These two type applications are equally generated.
- The total WiFi spectrum capacities of χ is 20 Giga bps.
- To reduce computation complexity, the amount of spectrum allocation is specified in terms of basic spectrum units (BSUs), where one BSU is the minimum amount (e.g., 512 Kbps in our system) of spectrum adjustment.
- We restrict NBS, EBS, AKSS and KSS models to the case of d_A = 0. Therefore, the utilities of disagreement points are zeros in our system.
- System performance measures obtained on the basis of 100 simulation runs are plotted as a function of the offered service request load.
- Performance measures obtained are normalized device’s payoff, system throughput, and fairness among APs in the WiFi tethering platform.
- For simplicity, we assume the absence of physical obstacles in the wireless communications.

B. RESULT ANALYSIS AND DISCUSSION
Fig.1 shows the normalized payoff of individual devices as the service task requests increase. In the point view of end-users, this performance criterion is a main concern. As mentioned above, the proposed scheme explores the interaction
of different bargaining solutions while leveraging the synergistic features. Under heavy traffic load situations, i.e., $\Lambda \geq 1.5$, our meta-bargaining approach can handle effectively the limited spectrum resource ($\chi$) for their corresponding mobile APs, and increases the individual user’s profit by an average of 15% than the CTWS, RRSM and MCIA schemes.

Fig.2 provides the comparison of system throughput for different WiFi tethering schemes. In our proposed scheme, the limited spectrum resource is fair-efficiently shared while inducing selfish mobile APs to operate their services. As a consequence of iterative two-phase bargaining process, we can exploit the current WiFi platform conditions, and adaptively allocate the spectrum resource to maximize the system throughput. Therefore, we can achieve an average of 15% higher system throughput than other existing protocols.

In order to effectively operate the WiFi tethering infrastructure, the fairness issue for each individual mobile APs is very important. To compare the fairness performance, we use the Jain’s fairness index, which is commonly used in network engineering to determine whether network agents are receiving a fair share of system resources. Our meta-bargaining approach can effectively compromise the contrasting viewpoints of different mobile APs. Therefore, under diversified traffic condition changes, i.e., $0.25 \leq \Lambda \leq 3$, our proposed scheme can improve the fairness index by an average of 20% than the existing CTWS, RRSM and MCIA schemes.

V. SUMMARY AND CONCLUSION

This paper proposes a novel spectrum allocation scheme for the mobile AP-controlled WiFi tethering process, which can make heterogeneous users gain certain profits after they participated in it. Designing such a WiFi spectrum allocation scheme is challenging due to a dynamically changing network traffic environment. To effectively handle this control problem, we adopt the four different bargaining solutions - NBS, EBS, AKSS and KSS, and employ the meta-bargaining approach to design our spectrum allocation scheme. By taking into account the different viewpoints of individual mobile APs, four bargaining solutions are sophisticatedly combined into the meta-bargaining game and act cooperatively and collaborate with each other in a cooperative manner. Therefore, the limited WiFi spectrum resource is effectively shared among different mobile APs while attempting to maximize the WiFi tethering performance. Finally, we conduct a simulation analysis, and verify the superiority of our meta-bargaining approach as compared with the existing CTWS, RRSM and MCIA protocols.

COMPETING OF INTERESTS

The author declares that there are no competing interests regarding the publication of this paper.

AUTHOR’S CONTRIBUTION

The author is a sole author of this work and ES (i.e., participated in the design of the study and performed the statistical analysis).

AVAILABILITY OF DATA AND MATERIAL

Please contact the corresponding author at swkim01@sogang.ac.kr.

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FIGURE 3. Fairness among mobile APs.