Efficient Rate Splitting Multiple Access Scheme based cooperative bargaining solutions

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ABSTRACT Due to the increasingly new communication technologies and growing traffic demands, dynamic spectrum allocation method becomes insufficient to guarantee the satisfaction of main wireless communication requirements such as spectrum and energy efficiency. In order to meet different requests, rate splitting multiple access (RSMA) has been recently presented as a generalized multiple access technique. In this study, we design a novel RSMA resource management scheme based on the cooperative bargaining game theory. According to the fundamental ideas of pessimistic utilitarian and optimistic max-min bargaining solutions, we can leverage a mutual consensus among different network users to improve the total system performance. Based on our interactive bargaining approach, the proposed scheme adaptively controls the spectrum and power resources in the RSMA system. To get a desirable fair-efficient solution, our bargaining strategy can make control decisions in a coordinated manner while ensuring the relevant trade-off between conflicting criteria. Under the diverse RSMA traffic scenario, the numerical simulation results demonstrate the efficiency of our proposed scheme over the existing state-of-the-art protocols. Finally, some open issues are spotted to shed lights on the need for further studies and future research efforts.

INDEX TERMS Rate splitting multiple access, Pessimistic utilitarian solution, Optimistic max-min solution, Cooperative Game model, Multiple access technique.

I. INTRODUCTION

The exponential growth of smart mobile devices and emergence of the Internet-of-Thing (IoT) paradigm has been a major driving force towards the evolution of wireless technologies. The aim of this is to ultimately support a plethora of new IoT services, such as extended reality, smart home, medical services, autonomous driving and tactile internet. To meet the demand for future data traffic services, academia, industry and regulatory agencies have focused on the research and development of novel network systems. Based on the full-duplex wireless transmission method in the communication process, it is necessary to transmit data at a rate of about 1,000 Mbps to users that exceeds their expectations. The vision of future networks is to build a large-scale connected complex system that can dynamically and rapidly respond to users’ service invocations. Until now, many researches have made valuable achievements through the use of new communication techniques and innovative ideas [1]-[2].

From the first to fourth generations (1G to 4G) of mobile communications, multiple access schemes have been the key technology that discriminates the capacities of wireless communications. Orthogonal multiple access (OMA) techniques harmonize the access of multiple users to the network, thus preventing the collision of transmissions from different users. Preserving the orthogonality between transmissions can be achieved such as frequency division multiple access (FDMA), time division multiple access (TDMA), and code division multiple access (CDMA); they were used in 1G, 2G and 3G, respectively. For fourth generation (4G) networks, orthogonal frequency division multiple access (OFDMA) has been developed for the multi-user access via assigning subset of carriers for each user. Therefore, the signals of different users could be mapped into orthogonal resources in the time-frequency domain to support multi-user access without severe inter-user interference. The approach improves wireless network performance by establishing independently modulating subcarriers within frequencies. The main principle of OMA techniques is separating user data steams to avoid inter-user interference and hence, achieves multiplexing gain with reasonable complexity [3]-[4].

As the era of the fifth generation (5G) of mobile communications, it is difficult for conventional OMA techniques to fulfill the requirements of the super-high data rate of smart mobile devices, ultra-low latency, ultra-reliable and massive connectivity. The non-orthogonal multiple access
(NOMA) technology is becoming a promising candidate to meet the aforementioned requirements of 5G mobile communication networks. The baseline idea of NOMA is to serve multiple users using the same resource in terms of time, frequency, and space. It can simultaneously transmit the signals of different users at the same time-frequency resource element, which is one subcarrier in one OFDMA symbol. Consequently, NOMA-based protocols can achieve higher spectrum efficiency than conventional OMA-based protocols. However, using NOMA protocols, individual users must decode all of the interference as they receive the messages, which significantly increases the computational complexity needed for signal processing [4]-[5].

To support more users in 5G networks, space division multiple access (SDMA) exploits the spatial separation between users to provide full time and frequency resources. As one of OMA techniques, SDMA employs linear precoding scheme to distinguish individual users in the spatial domain and fully depends on treating any residual multi-user interference as noise. By superposing users in the same time-frequency resources and separating them through spatial domain, this approach is capable of boosting the system spectrum efficiency. However, owning to the rate saturation, SDMA technique cannot support high-rate services or many users simultaneously. More recently, an alternative multiple access method, called rate splitting multiple access (RSMA), has been studied to compensate the disadvantages of NOMA and SDMA. For the next generation networks, RSMA is viewed as a technique to bridge the SDMA of treating interference as pure noise and the NOMA of decoding interference [3],[5]-[8].

Rate splitting technology has recently emerged in multi-antenna broadcast channel as a powerful and robust non-orthogonal transmission technique, and interference management strategy for wireless communications. Particularly, the message intended for each user is split into two parts: a common part and a private part. After jointly encoding the common and private parts at the transmitter, all superimposed data streams are broadcasted to all users. Each individual user can sequentially decode the common part, and it is removed. Then, the private part is decoded with the assistance of successive interference cancellation (SIC). Rate splitting technology grants all users the ability to partially decode the interference and partially treat the remaining interference as noise. By steering the power allocation between private and common parts, it is suitable for integrating with the multicast communication scenario for sixth generation (6G) wireless communications [6],[9].

Based on the rate splitting technique, RSMA is able to accommodate different users in a heterogeneous environment. As one of the leading 6G technologies, RSMA can address the challenges coming from NOMA and SDMA. Usually, spectrum efficiency and energy efficiency are fundamental indicators for the future communication system design; spectrum efficiency demonstrates the amount of data communications to be transmitted per unit of time, and energy efficiency represents the amount of data communications to be transmitted per unit of energy. Recent research results have shown that RSMA method outperforms other common multiple access methods, such as NOMA and SDMA, in terms of both spectrum and energy efficiency. However, implementing RSMA technique in future wireless networks also faces several challenges such as the split of common and private message, and resource management for effective private message transmissions [1],[5],[9].

In this study, our major goal is to design a new RSMA control scheme based on effective resource management strategies. The major challenge of our proposed scheme is to coordinate the different individual users while ensuring good global properties for common and private message transmissions. However, it is a complex and difficult work under dynamically changing wireless communication environments. Therefore, we need a new intelligent control paradigm and novel solution concept. In this paper, we adopt the concept of cooperative game theory to offer an effective control paradigm for RSMA communications. According to the idea of cooperative game theory, the resources of RSMA system are intelligently and coordinately managed to mediate between conflicting requirements. To the best of our knowledge, cooperative approach for the RSMA control scheme has not been well investigated.

A. TECHNICAL CONCEPTS

In recent years, mechanisms of cooperation in communication systems have attracted increasing attention from academia and industry. Such mechanisms require sharing the benefits among system agents based on some rational and obvious principles. In this regard, cooperative game theory provides a rich theoretical background for the analysis of sharing problems where participants, called game players, can make collective actions to obtain mutual benefits. Cooperative games consider situations where players conclude binding agreements to reach mutual benefits. Therefore, the key question to address is how to distribute the generated benefit by cooperation to game players. In this approach, an important assumption is made that the generated benefit can be easily distributed and shared among the players. This assumption allows formulating cooperation as a transferable utility game, and implementing well-established bargaining solution concepts from the cooperative game theory [10]-[11].

Most cooperative bargaining solutions proposed in the literature share the ideas of egalitarianism and utilitarianism. Egalitarianism states that equals should be given equal criteria problems. In fact, when using an additive value function to select a decision, an utilitarian principle is being applied, whereas egalitarianism is the motivation to use of max-min solutions. Recently,
many studies explore the bargaining solutions with respect to the criteria to solve the multi-criteria bargaining problems. Based on a compromise between the egalitarianism and utilitarianism, various bargaining solution concepts have arisen [12].

Multi-criteria bargaining solutions are concerned with situations in which a number of players must take into account several criteria, each of which depends on the decision of all players. When a vector of criterion weights is provided for the multi-criteria problem, the principles of egalitarianism and utilitarianism yield respectively to weighted max-min solutions, and to weighted utilitarian solutions. However, if only partial information about the importance of the criteria is available, a variety of solutions, which extend the utilitarian and the max-min solution, have been developed. In the viewpoint of utilitarianism, Pessimistic Utilitarian Bargaining Solution (PUBS) was developed based on the pessimistic rule, which has an inequality averse feature. With an egalitarian principle, Optimistic Max-min Bargaining Solution (OMBS) was proposed according to the optimistic rule, which is applied to select criterion weights [12].

B. MAIN CONTRIBUTIONS
In this study, we exploit the RSMA system infrastructure with the cooperative game theory, and develop a new RSMA control scheme. Based on the co-existence environment of common and private data streams, heterogeneous IoT devices share the limited system resource to maximize their payoff while considering energy and spectrum efficiency. To design a novel RSMA resource management scheme, our major objective is to guide selfish IoT devices toward a socially optimal outcome while enhancing the system performance. For satisfying this goal, multiple IoT devices work together and act cooperatively under dynamically changing network traffic conditions. Therefore, the proposed scheme is formulated as two cooperative games, and the fundamental ideas of PUBS and OMBS are adopted. In our scheme, control decisions are coupled with each other and dynamically adjustable in a step-by-step interactive manner. As far as we can gather, this is the first work that bargaining solutions are applied to the design of RSMA system’s control algorithm. The key contributions of this study are summarized as follows:

- We investigate the RSMA system platform to provide energy and spectrum efficient communication services. Under dynamic traffic environments, multiple IoT devices work together to strike an appropriate RSMA system performance.
- We study the basic concepts of PUBS and OMBS, and develop two bargaining game models to handle the common and private communication services. To dynamically adapt the current RSMA system conditions, control decisions are made in a step-by-step interactive bargaining manner.
- According to the PUBS, spectrum amounts for common and private streams are decided, and power levels for them are adjusted based the OMBS. Two bargaining solutions are reciprocally combined with each other to ensure the relevant trade-off between conflicting requirements.
- Through numerical results, we evaluate the performance of the proposed scheme, and demonstrate the superiority of our bargaining-based approach. In particular, we show the performance gain in terms of normalized system sum rate, power efficiency and device fairness as compared to that obtained with the existing state-of-the art protocols.

C. ORGANIZATION
The remainder of this paper is organized as follows. Section II reviews the related work. In Section III, we present the RSMA system infrastructure and formulate two cooperative bargaining models. Then, the principles and characteristics of PUBS and OMBS are presented. Based on these two bargaining solutions, we explain the proposed RSMA resource control algorithm in detail. In Section IV, simulations are carried out and the results are discussed. Finally, we conclude this article in Section V, along with future research directions.

II. RELATED WORK
Recently, RSMA technology is attracting the attention of the research community with particular attention to various wireless networking scenarios. In this section, we survey to summarize the up-to-date existing work related to the RSMA technique. The paper [14] considers employing rate splitting based transmission schemes in downlink cloud radio access network scenario with imperfect channel state information at the transmitter. In addition, the generalized rate splitting and special cases thereof are investigated, and a new scalable RS scheme is proposed. The numerical simulations demonstrate the significant gain of RS schemes compared to the state-of-the-art NOMA schemes, especially when the network becomes denser and when the fronthaul capacity resource is limited [14].

In [15], authors propose a multi-antenna dual-functional radar-communication system that enables the RSMA technique as well as joint transmission of communication streams and a radar sequence. The message split, precoders of communication streams and radar sequence are optimized together to jointly maximize weighted sum rate and minimize mean square error of beampattern approximation under the per-antenna power constraint [15]. The scheme in [16] is an efficient RSMA control algorithm that uses a linearly increasing number of common signals for a cloud radio access network downlink system. The decoding user devices of each common signal are carefully chosen using hierarchical clustering with inter-user equipment dissimilarity metric defined based on channel directions [16].
In [7], the Rate Splitting Multiple Access for Overloaded Networks (RSMA-ON) scheme is developed based on two transmission models in the realm of RSMA, namely, time partitioning (TP)-RSMA and power partitioning (PP)-RSMA. [7]. The TP-RSMA model independently serves the two groups of users over orthogonal time slots, and the PP-RSMA model jointly serves the two groups of users within the same time slot in a non-orthogonal manner. The PP-RSMA model can achieve the optimal degrees-of-freedom in an overloaded broadcast channel with heterogeneous channel qualities. Therefore, the PP–RSMA model gets explicit sum rate gain over the TP-RSMA model according to the benefits of power partitioning and RSMA. Furthermore, it is robust to channel inaccuracy and flexible to cope with quality rate constraints of all users. Finally, numerical results show that the PP-RSMA model becomes a powerful approach for the cellular IoT scenario as it is less sensitive to channel inaccuracy and achieves a higher spectrum efficiency [7].

G. Zhou et al. propose the Rate Splitting Multiple Access for Efficiency Tradeoff (RSMA-ET) scheme to boost the spectrum and energy efficiency tradeoff [9]. The tradeoff problem is a multiple-objective optimization problem and each objective function is non-convex due to the complex sum rate expressions and power consumption expressions. In addition, spectrum and energy efficiency maximization issues are two conflicting objectives. To tackle the challenges coming from multiple objective problem, the RSMA-ET scheme provides two models to transform the original problem into two single-objective problems, such as, weighted-sum problem and weighted-power problem. The weighted-sum problem is solved by maximizing the weighted sum of spectrum and energy efficiencies, and the weighted-power problem is solved to minimize the weighted sum of the inverse of both spectrum and energy efficiencies. Extensive simulation results show that the RSMA-ET scheme has a better adaptability in terms of both spectrum efficiency and energy efficiency and their tradeoff [9].

The paper [13] presents the Rate Splitting Multiple Access for Resource Allocation (RSMA-RA) scheme. To handle the resource allocation problem for the RSMA system, the RSMA-RA scheme consists of three algorithms. In the first algorithm, the non-convex problem of power distribution of a single subcarrier is transformed into a convex problem with the aid of difference of convex program; this problem is solved by its first-order Taylor expansion around a feasible point. In the second algorithm, the user-subcarrier matching problem is transformed into an assignment problem; this problem is solved by using Hungarian method. In the third algorithm, the power allocation problem is transformed into a Lagrange function and it is solved by an optimized power allocation method, which provide better sum-rate performance than equal power allocation. Via numerical results, the RSMA-RA scheme gains a higher system performance over conventional multiple access protocols [13].

Until now, some papers have studied important problems related to the RSMA system, and addressed several challenges such as the combination of common and private messages, and the power and spectrum control issues for effective private message transmissions. However, none of research literatures consider the multi-criteria interactive bargaining approach from a coordinated perspective. To the best of our knowledge, this is the first work that develops a novel bargaining approach to get a well-balanced system performance in the RSMA platform.

III. THE PROPOSED RSMA RESOURCE MANAGEMENT ALGORITHM

In this section, we set up the RSMA system platform, and derive basic concepts and expressions for the PUBS and OMBS. Then, two proposed bargaining game models are formulated to effectively manage the limited RSMA system resources. Finally, the main steps of our proposed algorithm are described in detail.

A. RSMA system platform and control problem formulation

In this paper, we consider a downlink multi-antenna multiuser wireless communication system. The network system consists of a set of multiple-antenna base stations (BSs), i.e., \( \mathbb{B} = \{B_1, \ldots, B_n\} \); they are positioned at different locations in a cellular network environment. Each BS is equipped with \( L > 1 \) antennas, and serves a group of single-antenna IoT devices, i.e., \( \mathbb{D}_B = \{D^B_1, \ldots, D^B_m\} \); they are randomly located in the \( B \)'s coverage area. In the RSMA system, the message \( \mathbb{M}_{B,D_j} \) intended for the \( D^B_{1 \leq j \leq m} \) is split into two parts where a common part \( \mathbb{M}^{C,B} \) and a private part \( \mathbb{M}^{P,B,D_j} \). The all devices’ common part is encoded into the common stream \( S^c_B \) using a codebook shared by all devices, i.e., \( D^B_{1 \leq j \leq m} \in \mathbb{D}_B \); the \( S^c_B \) is required to be decoded by all devices. The private part for the \( D^B_j \), i.e., \( \mathbb{M}^{P,B,D_j} \), is the remaining part of the message \( \mathbb{M}_{B,D_j} \); it is encoded into the private stream \( S^p_{D,j} \) for the \( D^B_j \). Fig.1 illustrates the RSMA platform architecture.
Each BS sends the transmitted signal, i.e., $\chi_B$, and the received signal at the $D_j^B$, i.e., $R_{D_j}^B$, are expressed as follows [5].

$$
\chi_B = \left(\sqrt{R_C} \times S_C\right) + \sum_{D_j^B \in D_B} \left(\sqrt{p_j^B} \times S_{D_j^B}\right) \\
R_{D_j}^B = \left(\frac{H_{D_j^B} \times \chi_B}{\sum_{D_k^B \in D_B} \left(p_k^B \times S_{D_k^B}\right)} + N_{D_j^B}\right) + \sum_{D_k^B \in D_B} \left(\frac{H_{D_k^B} \times p_k^B}{\sum_{D_k^B \in D_B} \left(p_k^B \times S_{D_k^B}\right)} \times S_{D_k^B}\right) + N_{D_j^B}
$$

(1)

where $p_c$ and $p_{D_j^B}$ are the transmit powers for the $S_C$ and $S_{D_j^B}$, respectively. $H_{D_j^B}$ represents the channel gain between the $D_j^B$ and $B$, and $N_{D_j^B}$ is the additive white Gaussian noise with variance $\sigma^2$. The achievable rate of the $D_j^B$ decoding common stream $S_C$, i.e., $C_{D_j^B}$, can be expressed as [5]:

$$
C_{D_j^B} = \\
A_{D_j^B} \times \log_2 \left(1 + \frac{R_{D_j}^B \times p_c}{\sum_{D_k^B \in D_B} \left(p_k^B \times S_{D_k^B}\right)} + \sigma^2\right)
$$

(2)

where $A_{D_j^B}$ is the assigned spectrum for the common stream $S_C$. After having decoded the $S_C$, each device can decode its private stream, the achievable private stream rate of $D_j^B$, i.e., $\gamma_{D_j^B}$, is given by [5]:

$$
\gamma_{D_j^B} = \\
A_{D_j^B} \times \log_2 \left(1 + \frac{R_{D_j}^B \times p_{D_j^B}}{\sum_{D_k^B \in D_B} \left(p_k^B \times S_{D_k^B}\right)} + \sigma^2\right)
$$

(3)

where $A_{D_j^B}$ is the assigned spectrum for the private stream, i.e., $S_{D_j^B}$. Finally, the total transmission rate of $D_j^B$, i.e., $T_{D_j}^B$, is estimated based on the common stream rate and achievable private stream rate where $T_{D_j}^B = C_{D_j^B} + \gamma_{D_j^B}$. In the viewpoint of $D_j^B$, the major goal is to maximize the $T_{D_j}^B$. However, communication resources in the RSMA system are limited. Therefore, effective resource control strategies should be considered to improve the spectrum and power efficiency. To address this control problem, we formulate two bargaining games, i.e., $G_A^B$ and $G_B^B$ for each $B$. It is noteworthy that these games are operated in a cooperative manner, and they are repeated in a step-by-step interactive fashion. The $G_A^B$ game decides the spectrum amounts for the $S_C$ and $S_{D_j^B}$ in $D_B$, i.e., $A_C$ and $A_{D_j^B}$. The $G_B^B$ game adjusts the power levels for the $S_C$ and $S_{D_j^B}$ in $D_B$, i.e., $p_c$ and $p_{D_j^B}$. Formally, we define the $G_A^B$ and $G_B^B$ game entities for each $B$, i.e., $G = \{G_A^B, G_B^B\} = \{B \in B, D_B \subset D\}$,

$$
\{G_A^B, S_{C}, S_{D_j^B} \in D_B, (A_C, A_{D_j^B}), U_{C}(\cdot), U_{D_j^B}(\cdot)\}, \\
\{G_B^B, S_{C}, S_{D_j^B} \in D_B, (p_c, p_{D_j^B}), U_{C}(\cdot), U_{D_j^B}(\cdot), T\}
$$

of gameplay.

- The $G_A^B$ and $G_B^B$ are mutually and reciprocally interdependent in an interactive manner, and they work together to allocate spectrum amounts and adjust power levels for common and private streams.
- $B$ is the set of BSs and $D$ is the set of total IoT devices in the RSMA system platform. $B$ is one BS in $B$, and $D_B$ is the subset of $D$; devices in $D_B$ are covered by the $B$.
- In the $G_A^B$, $S_C$ and $S_{D_j^B}$ are game players where $D_j^B \in D_B$, and $A_C$ and $A_{D_j^B}$ are their strategies, which are the allocated spectrum amounts for the $S_C$ and $S_{D_j^B}$, respectively. $U_{C}(\cdot)$ and $U_{D_j^B}(\cdot)$ are their utility functions.
- In the $G_B^B$, $S_C$ and $S_{D_j^B}$ are also game players like as the $G_A^B$. $p_c$ and $p_{D_j^B}$ are their strategies, which are the power levels for the $S_C$ and $S_{D_j^B}$, respectively. $U_{C}(\cdot)$ and $U_{D_j^B}(\cdot)$ are their utility functions.
- Discrete time model $T \in \{t_1, ..., t_c, t_{c+1}, ...\}$ is represented by a sequence of time steps. The length of $t_c$ matches the event time-scale of $G_A^B$ and $G_B^B$.

B. The fundamental ideas of PUBS and OMBS.
To characterize the fundamental ideas of PUBS and OMBS, the following notations will be used. Let \( \mathbb{R} \), \( \mathbb{R}_+ \) denote the set of all and non-negative real numbers, and \( \mathbb{R}^k \), \( \mathbb{R}_+^k \) are the \( k \)-fold Cartesian product of \( \mathbb{R} \) and \( \mathbb{R}_+ \), respectively. We use conventional notation for comparison of vectors: \( x \succeq y \) mean that \( x_i \geq y_i \), for all \( i = 1, 2, \ldots, k \). \( x > y \) indicates that \( x \succeq y \) and \( x \neq y \). \( x \gg y \) means \( x_i > y_i \) for all \( i = 1, 2, \ldots, k \).

We denote \( x \cdot y \) as the scalar product of the vectors \( x, y \in \mathbb{R}^k \), that is \( x \cdot y = \sum_{i=1}^{k} x_i y_i \). Let \( \Delta^k = \{ \lambda \in \mathbb{R}_+^k | \lambda \cdot 1^k = 1 \} \) denote the simplex in \( \mathbb{R}_+^k \) where \( 1^k \) is an \( k \)-dimensional vector with components equal to one. For a polyhedral subset \( \Lambda \subseteq \Delta^k \), let \( \text{ext}(\Lambda) \) denote the set of its extreme points, i.e., \( \text{ext}(\Lambda) = \{ \lambda \in \Lambda | \exists \lambda_1, \lambda_2 \in \Lambda, \lambda_1 \neq \lambda_2 \text{ and } \alpha \in (0,1) \text{ such that } \lambda = ((1-\alpha) \lambda_1 + \alpha \lambda_2) \} \) \cite{12}.

A multi-criteria problem with partial information is represented by a triplet \((X, z, \Lambda)\), where i) \( X \subseteq \mathbb{R}^n \) is the set of feasible points in the decision space, each \( x \in X \) is an \( n \)-dimensional vector of decision variables; ii) \( z : \mathbb{R}^n \to \mathbb{R}_+^k \) is a vector function, whose \( k \) components, \( z_1(x), \ldots, z_k(x) \), are \( k \) scalar functions of the decision vector \( x \) which represent the criteria that have to be taken into account to evaluate each feasible decision; iii) \( \Lambda \subseteq \Delta^k \) is a polyhedron of weights, which represent the information available with respect to the importance of the criteria. A solution for the class of multi-criteria problems is a map, \( F \), which associates a subset of \( X \) to each problem \((X, z, \Lambda) \in \mathcal{P} \) where \( \mathcal{P} \) is the class of these multi-criteria problems, and \( F(X, z, \Lambda) \subseteq X \). Therefore, a solution is single-valued in \( \mathcal{P} \) if for all \((X, z, \Lambda) \in \mathcal{P} \) \cite{12}.

The PUBS is developed based on the idea that the evaluation of a decision may depend on the minimum weighted value among all the feasible weights in \( \Lambda \). In the PUBS, the minimum feasible value assigned to a decision across the whole set of weights is maximized. Therefore, the PUBS is characterized as a solution for single-criterion optimization problems which depend on the extreme points of the polyhedron of weights. Note that this problem is linear provided that \( X \) is a polyhedron and \( z \) are linear criteria functions. Mathematically, the PUBS for each \((X, z, \Lambda) \in \mathcal{P} \), i.e., \( F_{\text{PUBS}}(X, z, \Lambda) \), is defined as follows \cite{12}:

\[
F_{\text{PUBS}}(X, z, \Lambda) = \arg \max_{x \in X} m_{\Lambda}(x) = \arg \max_{x \in X} \left[ \min_{\lambda \in \Lambda} \left( \sum_{i=1}^{k} (\lambda_i \times z_i(x)) \right) \right]
\] \hspace{1cm} (4)

The OMBS is designed according to the concept that the evaluation of a decision depends upon its worst performance across all the criteria but selecting the best of this minimum across all feasible weighting vectors. Therefore, the OMBS is the weighted max-min solution, which corresponds to the vectors in \( \Lambda \) that give the best max-min values. Formally, the OMBS for each \((X, z, \Lambda) \in \mathcal{P} \), i.e., \( F_{\text{OMBS}}(X, z, \Lambda) \), is defined as follows \cite{12}:

\[
F_{\text{OMBS}}(X, z, \Lambda) = \arg \max_{x \in X} \left[ \min_{i=1, \ldots, k} \left( \frac{z_i(x)}{\lambda_i} \right) \right]
\] \hspace{1cm} (5)

\[\text{C. TWO BARGAINING GAME MODELS FOR THE RSMA SYSTEM}\]

To develop our RSMA resource management scheme, we construct \( \mathbb{G}_A^B \) and \( \mathbb{G}_B^B \) games. They are interacting with each other during the spectrum and power control process. To maximize the RSMA system performance, the \( \mathbb{G}_A^B \) decides the values of \( A_{CB} \) and \( A_{D_{ij}} \) which are the allocated spectrum amounts for the \( S_{CB} \) and \( S_{D_{ij}} \) respectively. At each time period, \( U_{CB}(\cdot) \) and \( U_{D_{ij}}(\cdot) \) in the \( \mathbb{G}_B^B \) are defined as follows:

\[
\begin{align*}
U_{CB}(A_{CB}, M_{CB}) &= \exp \left( \alpha + \log \left( \frac{\min (A_{CB}, M_{CB})}{M_{CB}} \right) \right) \\
U_{D_{ij}}(A_{D_{ij}}, M_{D_{ij}}) &= \log \left( \exp \left( \frac{\min (A_{D_{ij}}, M_{D_{ij}})}{M_{D_{ij}}} \right) \right)^{\beta} \\
\end{align*}
\] \hspace{1cm} (6)

\[
s.t., \quad \mathbb{R}_B = A_{CB} + \sum_{D_{ij} \in \mathbb{D}_B} A_{D_{ij}}
\]

where \( M_{CB} \) and \( M_{D_{ij}} \) are the requested spectrum amounts for the \( S_{CB} \) and \( S_{D_{ij}} \), respectively. \( \alpha \) is a control parameter for the \( U_{CB}(\cdot) \), and \( \beta \) is a control parameter for the \( U_{D_{ij}}(\cdot) \). \( \mathbb{R}_B \) is the total spectrum amount for the \( \mathbb{B} \). To adaptively allocate the spectrum for each stream, we can consider two criteria; delay sensitivity and packet loss intolerance, which will be set up for each individually services. Therefore, the criteria vector \( \Lambda \) for the \( \mathbb{G}_A^B \) consists of these information. To maximize the spectrum efficiency, the solution concept should be strongly concerned the utilitarianism. In this case, the PUBS is preferred for the solution concept of \( \mathbb{G}_A^B \). It is given by:

\[
[\mathbb{G}_A^B]_{\text{PUBS}} \left( \left( U_{CB}(\cdot), U_{D_{ij}}(\cdot), (A_{CB}, A_{D_{ij}}), \mathbb{G}_A^B \right) \right) = \arg \max_{A_{CB}, A_{D_{ij}} \in \mathbb{D}_B} \left[ \min_{\mathbb{A} \in \mathbb{A}} (U) \right]
\] \hspace{1cm} (7)
where $\lambda_{C_B}$ and $\lambda_{D_j^B}$ are weight factors in the $A_{C_B}$ for $C_B$ and $D_j^B$ communication services, respectively. Contrast to the $G_A^B$, the $G_P^B$ game is operated to set the power levels for game players. As game player, the utility function of $C_B$ and $D_j^B$, i.e., $U_{C_B}(\cdot)$ and $U_{D_j^B}(\cdot)$, are defined as follows:

$$U_{C_B}(p_{C_B}, \Gamma_{C_B}) = \eta \times \left( \exp \left( \frac{\min(p_{C_B}, \Gamma_{C_B})}{I_{C_B}} \right) - \exp \left( - \frac{\min(p_{C_B}, \Gamma_{C_B})}{I_{C_B}} \right) \right) - \mu$$

$$U_{D_j^B}(p_{D_j^B}, \Gamma_{D_j^B}) = \tau \times \left( \log \left( \frac{\min(p_{D_j^B}, \Gamma_{D_j^B})}{I_{C_B}} \right) - \log \left( - \frac{\min(p_{D_j^B}, \Gamma_{D_j^B})}{I_{C_B}} \right) \right) + \varphi$$

subject to $\Psi_B = p_{C_B} + \sum_{D_j^B \in D_B} p_{D_j^B}$

where $\eta$ and $\mu$ are control parameters for the utility function of $C_B$, and $\tau$ and $\varphi$ are control parameters for the utility function of $D_j^B$. $\Psi_B$ is the total power energy of $B$. In this study, it is defined as a conceptual power unit. To adjust the power levels for each stream, we also make decisions according to the same performance criteria. Therefore, the $A$ for the $G_P^B$, i.e., $A_{G_P^B}$, is defined as the same manner as the $A_{G_A^B}$. In the $G_P^B$, the power levels of game players should be decided by considering the relative fairness. In this case, the $OMBS$ is preferred for the solution concept of $G_P^B$. It is given by:

$$[G_P^B]_{OMBS} \left( \left( U_{C_B}(\cdot), U_{D_j^B}(\cdot), p_{C_B}, p_{D_j^B}, A_{G_P^B} \right) \right) = \max_{p_{C_B}, p_{D_j^B}} \left[ \left. \min_{A_{C_B}, A_{D_j^B}} \left( \left. \left( \sum_{D_j^B \in D_B} \frac{U_{C_B}(\cdot) - U_{D_j^B}(\cdot)}{A_{C_B}} \right) \right) \right] \right]$$

$$= \arg \max_{p_{C_B}, p_{D_j^B}} \left[ \min_{A_{C_B}, A_{D_j^B}} \left( \left. \left( \sum_{D_j^B \in D_B} \frac{U_{C_B}(\cdot) - U_{D_j^B}(\cdot)}{A_{C_B}} \right) \right) \right]$$

D. MAIN STEPS OF OUR RSMA RESOURCE MANAGEMENT ALGORITHM

In this article, we propose a novel RSMA resource management algorithm to characterize the common and private message streams. To find the best fair-efficient solution, we adopt the ideas of PUBS and OMBS. To decide the spectrum amounts for the $S_{C_B}$ and $S_{D_j^B \in D_B}$, the $G_A^B$ game model is formulated, and the PUBS is used to solve the spectrum allocation problem. To adjust the power levels for the $S_{C_B}$ and $S_{D_j^B \in D_B}$, the $G_P^B$ game model is developed, and the OMBS is employed to solve the power adjustment problem. In each base station, the $G_A^B$ and $G_P^B$ games are worked repeatedly in a step-by-step online manner, and they are operated in a parallel fashion. Owing to the desirable characteristics of the PUBS and OMBS, we can effectively satisfy contradictory requirements of game players under dynamic RSMA system environments.

In this study, we do not focus on trying to get an optimal solution based on the traditional optimal approach. But instead, the decision mechanism in our dual-interactive bargaining model is implemented with polynomial complexity. From the view-point of practicality, it is a suitable approach for real world system operations. If we assume that $m$ is the total number of IoT devices in each base station, $k$ is the number of available units for the spectrum allocation, and $l$ is the total number of power levels, the time and space complexity of our proposed scheme can be summarized in Table I.

| Game model | Time complexity | Space complexity |
|------------|----------------|-----------------|
| $G_A^B$    | $O(k \cdot m \log m)$ | $O(k \cdot m)$ |
| $G_P^B$    | $O(l \cdot m \log m)$ | $O(l \cdot m)$ |
| Total      | $O((l + m) \cdot \log m)$ | $O((k + l) \cdot m)$ |

The main steps of the proposed algorithm can be described as follows, and they are described by the following flowchart:

**Step 1:** To share the spectrum and power resources in the RSMA system, the values of the control factors and parameters are listed in Table II, and the simulation tested is given in Section IV.

**Step 2:** For each IoT device, traffic services are generated in the $B$. They are split into $S_{C_B}$ and $S_{D_j^B \in D_B}$ by using the RSMA technology.

**Step 3:** In each $B \in B$, the $G_P^B$ game is operated in a dispersive manner. In this game, the $S_{C_B}$ and $S_{D_j^B}$ are game players, and their utility functions, i.e., $U_{C_B}(\cdot)$ and $U_{D_j^B}(\cdot)$, are defined according to (6).
Step 4: The concept of PUBS is determined using (4). For the $G_B^P$ game, the players’ strategies, i.e., $A_{CB}$ and $A_{DP}^{B}$, are determined based on the equation (7).

Step 5: In each $B \in B$, the $G_P^B$ game is also operated in a distributed fashion. In this game, the $S_{CB}$ and $S_{D}^{B}$ are game players, too, and their utility functions, i.e., $U_{CB}(\cdot)$ and $U_{D}^{B}(\cdot)$, are defined according to (8).

Step 6: Using (5), the idea of OMBS is given. For the $G_P^B$ game, the players’ strategies, i.e., $p_{CB}$ and $p_{D}^{B}$, are determined based on the equation (9).

Step 7: During discrete time periods, the $G_B^P$ and $G_P^B$ games work together and act cooperatively to get the optimal performance in the RSMA system.

Step 8: Constantly, game entities in the $G_B^P$ and $G_P^B$ self-monitor the current RSMA platform environments, and explore to achieve mutual advantages in a coordinated manner. Proceed to Step 2 for the next game process.

- The simulated RSMA system platform consists of base stations in $B$ and multiple IoT devices in each $B$ where $|B| = 5$ and $|D_B| = 10$. Devices are located in the area covered by $B$.
- Total spectrum capacity ($\mathfrak{R}_B$) of each $B$ is 100 Gbps.
- To reduce computation complexity, the amount of spectrum allocation process is specified in terms of basic spectrum units (BSUs), where one BSU is the minimum amount (e.g., 4 Mbps in our system) of spectrum allocation.
- $p_{CB}$ and $p_{D}^{B}$ are decided based on the normalized power levels where $p_{CB}, p_{D}^{B} \in [p_{min}, p_{max}]$; $p_{min}$ and $p_{max}$ are the pre-defined minimum and maximum power levels, respectively.
- The total power energy of $B$ ($\mathfrak{P}_B$) is defined as a conceptual value, and $p_{CB}$, $p_{D}^{B}$ are increased (or decreased) by multiples of $\Delta p$. We set $\mathfrak{P}_B = 7$ and $\Delta p = 0.1$ in this paper.
- Wireless communication tasks are generated for each individual IoT device. At each time epoch, the generation process for task services is Poisson with rate $A$ (services/t), and the range of offered workload was varied from 0 to 3.0.
- Six different communication task services are assumed based on their communication requirements, and service duration times.
- Each communication service has its own delay-sensitivity and packet loss intolerance. This information is used to define the criteria vectors $A_{\alpha}^B$ and $A_{\mathfrak{P}}^B$.
- System performance measures obtained on the basis of 100 simulation runs are plotted as a function of the offered task request workload.

**TABLE II**

| Parameter | Value | Description |
|-----------|-------|-------------|
| $n$ | 5 | the total number of base stations |
| $m$ | 5 | the total number of IoT devices in each base station |
| $\alpha$ | -0.8 | a control parameter for the $U_C$ (·) |
| $\beta$ | 1.3 | a control parameter for the $U_C$ (·) |
| $\mathfrak{R}_B$ | 100Gbps | total spectrum amount for each base station |
| $\eta$, $\mu$ | 0.5, 1 | control parameters for the $U_C$ (·) |
| $\tau$, $\varphi$ | 1.2, 1 | control parameters for the $U_C$ (·) |
| BSU | Mbps | the minimum amount of spectrum allocation |
| $p_{CS}$ | [0.2 ~ 1] | the range of power levels for a common stream |
| $p_{PS}$ | [0.1 ~ 1] | the range of power levels for a private stream |
| $\Delta p$ | 0.1 | the variance unit value for power levels |
| $\mathfrak{P}_B$ | 7 | total power energy of each base station |
| Service Type | Sensitivity | Intolerance | Spectrum Req. | Service duration |
|--------------|-------------|-------------|---------------|------------------|
| Common part  | I           | 0.8         | 0.6           | 156 Mbps         | 20 t             |
|              | II          | 0.6         | 0.9           | 64 Mbps          | 25 t             |
|              | III         | 0.5         | 0.8           | 32 Mbps          | 30 t             |
| Private part | IV          | 0.7         | 0.75          | 128 Mbps         | 35 t             |
|              | V           | 0.9         | 0.5           | 48 Mbps          | 40 t             |
|              | VI          | 0.75        | 0.7           | 256 Mbps         | 15 t             |

Fig. 2 shows the normalized system sum rate versus different RSMA workload ratios. In our simulation model, the normalized system sum rate can be interpreted as the system throughput. From this figure, we can see that our proposed scheme always achieves the best performance among all schemes. This is due to the fact that our interactive bargaining approach can effectively handle the limited spectrum and power resources to transfer the common and private messages between base station and IoT devices. Therefore, based on the current information, we can adapt the dynamics of RSMA system under widely different traffic situations.

Fig. 3 shows the performance comparison in terms of power efficiency in the RSMA system. From the curves in Fig. 3, we can see that the power efficiency linearly decreases while increasing service workload. Intuitively, as the service workload increases, it may create a traffic congestion in the RSMA network, which causes lower power efficiency owing to the interference of wireless communications. Compared with the existing RSMA-ON, RSMA-ET and RSMA-RA schemes, our proposed scheme can maintain a higher power efficiency from low to heavy traffic-load distributions. The reason is that our bargaining approach can strike an appropriate power balance between different services while leading to an optimized system performance.

To verify the device fairness in the RSMA system, we provide the simulation results in Fig. 4. From this figure, we can see that our proposed scheme can achieve the best fairness than other existing protocols for the range of offered workload rates. Traditionally, one of the main questions in cooperative game theory is how to allocate in some fair way the limited resource for the players. The answer to this question is bargaining solutions; they are paradigmatic for the fairness issue. The major characteristic of PUBS and OMBS is to provide a fair-efficient solution with taking the mutual advantages. This feature ensures a preferable outcome in the fairness comparison. The simulation results shown in Fig. 2 to Fig. 4 demonstrate that our proposed scheme can give adaptability and flexibility to solve the RSMA resource management problem while maintaining a well-balanced system performance between conflicting requirements.

V. SUMMARY AND CONCLUSIONS

For future networks, the RSMA technology is a general and effective multiple access method. To achieve a desired RSMA system performance, resource management plays a key role. In this paper, we have addressed the multi-criteria resource management problem in the RSMA system. To solve this
problem in an efficient way, the bargaining concepts borrowed from PUBS and OMBS are observed, and we formulate two cooperative game models. Our approach can leverage a mutual consensus to strike an appropriate performance balance between spectrum and power efficiency. During our interactive bargaining process, we can effectively manage the limited RSMA system resources under widely different service task intensities. Finally, we perform extensive experimental simulations to prove the effectiveness of our proposed method. As has been revealed in the numerical results, it is concluded that the proposed scheme can achieve performance gains compared to the currently developing RSMA-ON, RSMA-ET and RSMA-RA schemes.

Our future work will involve conducting experiments to test the validity and performance of our proposed method on a real RSMA platform testbed. It means our future work includes the performance demonstration of RSMA by real infrastructure prototypes. In addition, we aim to integrate the security issues into the RSMA communications. In the direction of this approach, we will investigate the secure precoder design in RSMA-based broadcast channels. Taking user security requirements and power constraint into consideration, we will formulate an instantaneous weighted sum-rate maximization problem. Besides, we can investigate AI-based machine learning techniques to optimize the RSMA system performance. Especially, we will develop a Markov decision process model to formulate the dynamic of the communication channel in the RSMA network. Then, the deep reinforcement algorithm will be proposed to find the optimal power allocation policy for the transmitter without requiring any prior information of the channel.

ACKNOWLEDGMENTS
This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2021-2180-01799) supervised by the IITP (Institute for Information & Communications Technology Planning & Evaluation), and was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No.2021R1F1A1045472).

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

AUTHOR' 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
The data used to support the findings of this study are available by contacting the corresponding author at swkim01@sogang.ac.kr.