Bargaining Game Based Time Scheduling Scheme for Ambient Backscatter Communications

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ABSTRACT Backscatter communications have been acknowledged as an essential key technology in the Internet of Things (IoT) applications. Considering the fact that it needs the coordination from network agents, cooperative bargaining theory is an effective method to strike an appropriate system performance. In this paper, we investigate time scheduling algorithms for a backscatter-aided radio-frequency (RF) powered cognitive radio (CR) network, where multiple secondary transmitters can switch among the backscatter, the energy harvest, and active data transmission modes. Our objective is to maximize the RF-CR system performance while exploring the mutual benefits to leverage a reciprocal consensus between different control issues. According to the ideas of two different bargaining solutions - modified Nash bargaining solution and equitable Nash bargaining solution, we design a new dual bargaining game model to effectively share the limited time resources. The main novelty of our proposed approach is its adaptability, flexibility and responsiveness to current RF-CR system conditions. At last, numerical simulations are carried out to evaluate the performance of the proposed scheme, and we demonstrate the benefits of our dual bargaining game approach.

INDEX TERMS Backscatter communications, Internet of Things, harvest-then-transmit, cognitive radio, cooperative bargaining theory.

I. INTRODUCTION We have been witnessing the growth of wireless communication technologies over the last decades. Evolution from 1G to 4G networks has shown many challenges in both physical designs and their fields of applications. With today’s rapid development of communication technology, the ultra-dense Internet of Things (IoT) is a key application paradigm for the forthcoming fifth-generation and future wireless network systems. It is predicted by Ericsson that about 22.3 billion IoT devices will be deployed worldwide by 2024, and the number will be over 80 billion worldwide by 2030. Therefore, the boom of IoT paradigm in 5G networks will be a game changer in the future generation, and has boosted the attention in the emergence of many new technologies to meet different service requirements. It will open a door for new wireless architecture and smart services. To promote intelligent services, we should ensure the ubiquitous connectivity of wireless IoT devices to monitor, generate data, and process the data timely [1], [2].

With the explosive surge of resource-intensive IoT applications, the development of massive IoT devices is facing different challenges. First of all, the battery capacity of the IoT device is usually very small due to the stringent device size constraint. It causes the limited operation time of the IoT device. In addition, smart IoT devices have led to an increasing spectrum demand in modern wireless networks. Therefore, making the IoT devices consuming as little power as possible to transmit communication data is very important. To tackle this challenge, we should consider new and novel energy harvesting and spectrum sharing methods, which would be a more practical and comprehensive way compared to the traditional energy and spectrum control approaches [3], [4].

Cognitive Radio (CR) is a concept introduced to address the upcoming spectrum sharing issue. It dynamically empowers the secondary transmitters (STs) to utilize the underused spectrum without causing any interference to the primary transmitter (PTs). Therefore, it has been acknowledged as a promising technique to meet the demand of the tremendous increasing spectrum demands. Among various CR technologies, the radio-frequency (RF) powered CR network has
received growing attention with the rapid progress of the RF energy harvesting technique. A clear advantage of this technique is that IoT devices can harvest energy from consistently available RF sources to prolong and sustain the operations of them. When a PT is busy, multiple STs harvest energy from the RF signal emitted by the PT. If a PT is idle, STs utilize the harvested energy to transmit their data to the secondary gateway (SG). As a result, the RF-powered CR (RF-CR) system not only improve the spectrum efficiency, but also increase the energy efficiency [5], [6].

In the RF-CR system, the actual data transmission is usually organized in a harvest-then-transmit manner. Usually, the performance of STs is mainly dependent on the activity of PTs. In particular, the activity of PTs is expected to be kept at a mild level to guarantee a satisfying performance of STs. Otherwise, the total transmitted bits by the STs may be significantly reduced. To overcome this disadvantage, there has recently been an emerging interest in backscatter communications. It is a wireless communication paradigm that allows a secondary backscatter device to superimpose its information-bearing data on a primary signal, without requiring any type of power-consuming active components or other signal conditioning units. Therefore, this technology allows IoT devices to transmit data by reflecting incident RF signals. In addition, devices do not need power-consuming and expensive radio analog components (including RF oscillators, amplifiers, and filters), since they modulate information by reflecting RF signals. With the backscatter technology, STs can transmit data by backscattering PT signals when the PT is busy. Recently, it has been acknowledged as an essential supplement to improve the performance of RF-CR systems and integrating the backscatter communication technology to the RF-CR system is attracting an increasing research interest [4], [6], [14].

In the backscatter-aided RF-CR system setting, there usually exist multiple STs transmitting their data to the SG. It is notable that the SG is responsible for notifying the STs about the state of the primary channel. Each ST does not need the participation of the SG when it harvests energy, but the ST needs the cooperation from the SG when it transmits its data using the backscatter communication technology. Individual STs can switch between the harvest-then-transmit (HTT) mode and the backscattering mode for their own data transmission. When the channel is occupied by PTs, STs cannot transmit their data. However, at a given time instance, it is able to either harvest energy from the PT’s signal or backscatter the PT’s signal for its own data transmission with a relatively lower bitrate. Therefore, the secondary transmission is executed in the time-division multiple access (TDMA) manner, and each time slot can be used as energy harvesting, backscattering or ST data transmission [4], [6].

With more and more IoT devices connected to the RF-CR system, it may not satisfy all the transmission demands of multiple STs. Based on the TDMA method, the time slot is extremely valuable and scarce resource, and it may not satisfy all the transmission demands of STs. Usually, service requirements are different for each individual ST. Therefore, STs need the time resources differently, and the SG is more likely to assign adaptively the time slots to multiple STs, which bring more social welfare to the RF-CR system. Based on different characteristics, the STs have different control strategies. However, they should work together toward an optimal RF-CR system performance. Therefore, in this study, we adopt a cooperative bargaining game paradigm to design a fine-grained time scheduling algorithm for the RF-assisted CR network platform [5].

A. Technical Concepts

Almost seventy years ago, J. Nash studied a cooperative bargaining theory and published his pioneered seminal paper about the static axiomatic approach, which is called the Nash bargaining solution. It describes the bargaining problem by using only the information contained in a set of utility functions, which represent the players’ preferences, and the status quo, called the disagreement point. The Nash bargaining solution has become one of the most fruitful paradigms of how to share the created surplus among players in a fair way. However, even though Nash’s idea is the founding stone of bargaining process, and inspires a large literature on axiomatic solutions and applications, some features have been criticized in the subsequent years. Since then, several new bargaining solutions have been introduced to make up for the weak points of the original Nash solution [7], [8].

Recently, A. Nazari et al. propose the modified Nash bargaining solution (MNBS) to implement the cooperative framework in a fair manner. The conventional Nash bargaining solution results in equal surpluses for all players. However, to provide a fair bargaining solution, the MNBS can ensure that players who pay more for investments would receive higher surpluses. Especially, each game player takes a quota of shared investment costs in a way that all participating players benefit from the cooperation. In 2019, Y. Xu and N. Yoshihara refine the original Nash solution by incorporating equity and efficiency considerations. The proposed refinement is called the equitable Nash bargaining solution (ENBS), which is defined as the composition of the Nash solution and a variant of the Kalai-Smorodinsky bargaining solution. Based on the equity principle, the ENBS selects the maximizing outcome in which the ratios of all players’ utility gains with respect to their maximum attainable utilities are equalized [9], [10].

B. Main Contributions

In this study, we exploit the cooperative data transmission mechanism with the backscatter technology. Based on the backscatter-aided RF-powered CR system infrastructure, our major objective is to maximize the system throughput under dynamically changing system environments. To satisfy this goal, each individual ST can switch adaptively between HTT and backscatter modes. To effectively handle this switching problem, we adopt the idea of ENBS. When a primary channel is idle, multiple STs transmit their data actively. Based on
the concept of MNBS, the idle time period is shared by STs. According to the ENBS and MNBS, we design a new dual bargaining game model, which can play a significant role in determining system performance. During the interactive and iterative processes, control decisions are made to share the limited time slots; our time scheduling strategies are coupled with each other to approximate an optimized system performance. To the best of our knowledge, this is the first work that applies two different bargaining solutions to the design of RF-CR system control algorithm. The key contributions of this paper are summarized as follows:

- We introduce the RF-CR network infrastructure and establish the system model to operate the limited time resources. Under widely different and diversified network environments, individual STs participate in the different communication modes in a cooperative manner.
- We study the fundamental idea of the ENBS and MNBS to design our dual bargaining game model. Based on the main characteristics of RF-CR system platform, we formulate two different bargaining games to ensure the relevant trade-off between efficiency and fairness issues.
- The ENBS is used to switch between HTT and backscatter modes, and the MNBS is adopted to dynamically schedule the time resources for the active ST data transmission. These two solutions lead to a reciprocal consensus in the challenging time scheduling problem.
- In our dual bargaining game process, control decisions are coupled with each other to get a desirable system solution. In a coordinated manner, we consider the current information to provide more efficient control over system condition fluctuations.
- By extensive simulations, we evaluate and compare the performance between our proposed scheme and the existing state-of-the-art protocols. A performance comparative study provides useful guidance to confirm the superiority of our proposed dual bargaining game approach.

C. ORGANIZATION

The remainder of this paper is organized as follows. Section II reviews the related work. In Section III, the RF-CR system platform and our dual bargaining game are formulated. Then, the principles and characteristics of ENBS and MNBS are presented. Based on these two solutions, we design our time scheduling algorithm for the backscatter-aided RF-powered CR system. Section IV presents the extensive simulation results to verify the effectiveness of our proposed approach. Finally, Section V concludes the paper with a summary of the contribution, and draws future research directions.

II. RELATED WORK

With the rapid development of backscatter technology, the RF-powered CR network paradigm is a new concept that has the potential to play a key role in meeting the requirements of future networks. Over the past few years, this platform has attracted growing interests. W. Wang et al. propose the Stackelberg game based Distributed Time Scheduling (SDTS) scheme. They consider a multi-user CR network with hybrid STs that are jointly powered by RF-energy harvesting and backscattering techniques. Therefore, multiple STs are able to transmit their data using the HTT and backscatter modes. To optimally allocate the limited system resources, they model the joint transmit-mode selection and time resource allocation problem as a constrained non-cooperative game among the STs. In particular, the interaction between the primary and secondary networks is formulated as a single-leader-multi-follower hierarchical Stackelberg game. Based on the analysis of this game properties, the SDTS scheme proposes a distributed and iterative allocation strategy searching mechanism which is guaranteed to converge to the Stackelberg Equilibrium as well as the social optimality among STs. Finally, the simulation results demonstrate the effectiveness of the SDTS scheme [6].

The paper [11] designs the Wireless Powered Backscatter Communication (WPBC) scheme by including a hybrid access point and multiple users. For the multi-user RF-powered wireless network, a new model is developed while employing both HTT and backscatter modes. These two modes are employed by users to improve the system performance. To maximize the sum-throughput, one fundamental optimization problem is formulated based on the transmission policy, which includes the optimal working mode permutation and time allocation strategies. In addition, the impact of user’s schedule order is investigated to affect the time allocation policy; it influences the sum-throughput. The simulation results have confirmed that the WPBC scheme achieves a larger sum-throughput than that of traditional protocols [11].

In [12], the Powered Backscatter-assisted Throughput Fairness (PBTF) scheme has been developed as a max-min throughput based resource allocation protocol. For a wireless powered IoT network, this scheme ensures the fairness among STs, which harvest energy and convey their information by the backscattering technology. To solve the throughput fairness problem, a max-min throughput based non-convex problem is formulated and it is transformed into a convex problem by introducing a series of auxiliary variables. The mathematical analysis reveals that the max-min throughput is achieved when each ST consumes all the harvested energy and works in the hybrid of backscattering and HTT modes. Simulation results are presented to show that the PBTF scheme achieves a much better throughput fairness while maintaining almost the same average throughput compared to the existing protocols [12].

Until now, some resource allocation schemes have proposed with novel ideas for the RF-powered CR platform. Instead of the existing protocols, the main contribution of our scheme lies in the resource allocation strategy. To the best of our knowledge, this is the first work to design a dual bargaining game model by jointly considering the ENBS and MNBS. Due to the desirable characteristics of cooperative game theory, our hybrid bargaining approach can get a
globally desirable RF-CR system performance while dynamically adapting the backscatter-aided network environment.

III. THE PROPOSED RF-CR SYSTEM CONTROL SCHEME

In this section, we first briefly introduce the RF-CR network platform environment. Then, we describe the concept of the ENBS and MNBS. Finally, the proposed RF-CR system time sharing algorithm is presented based on our dual bargaining game approach.

A. BACKSCATTER-AIDED CR PLATFORM AND DUAL BARGAINING GAME

In this paper, a backscatter-aided RF-CR system model is taken for analysis. There are one PT \( (\mathcal{P}_T) \), one SG \( \{S_G\} \), and \( n \) STs, that is, \( \mathcal{D} = \{D_1, \ldots, D_n\} \), as shown in Fig.1. \( \mathcal{P}_T, S_G \) and \( \mathcal{D}_{1 \leq i \leq n} \) are equipped with omnidirectional antennas, and STs are located within a coverage area of the \( S_G \).

In the primary network, the channel state is divided into the busy \( (T^B) \) and the idle \( (T^I) \) periods depending on whether the PT emits signals or not. In the secondary network, the TDMA method is employed to avoid interference. Therefore, secondary transmission is executed in time slots. When the channel is occupied by the primary transmission, STs can either harvest energy from the PT’s signal or backscatter the PT’s signal for their own data transmission. If the channel is idle, STs can transmit their data to the SG actively [4]–[6].

Each ST \( \{D_{1 \leq i \leq n}\} \) consists of a controller, a backscatter circuit, an energy harvesting module, a transmission data allocator, and a rechargeable battery. Note that the actions of ST are dependent on the channel state of the primary network. In particular, during the \( T^B \) period, the ST can backscatter ambient signals or harvest energy, which is selected by its controller. The length of \( T^B \) is evenly divided by multiple time slots, and each time slot is assigned to each ST; the time slot \( \tau_i \) is allocated to the \( D_i \) where \( T^B = \sum_{D_{1 \leq i \leq n}} \tau_i \). The \( \tau_i \) is split by two time sub-slots; that is, \( \frac{(1 - \rho_i) \cdot \tau_i}{\rho_i \cdot \tau_i} \) is used to harvest energy and \( \frac{\rho_i \cdot \tau_i}{(1 - \rho_i) \cdot \tau_i} \) is used to backscatter ambient signals to the \( S_G \). To effectively adapt the current backscatter-aided communication environments, each \( \rho_i \) value should be dynamically adjusted. On the one hand, during the \( T^I \) period, the \( S_G \) schedules the time slots to meet the data transmission demands of STs. To maximize the RF-CR system throughput, the time scheduling mechanism of \( S_G \) must ensure a relevant tradeoff between efficiency and fairness. The channel frame structure for the \( T^B \) and \( T^I \) periods are illustrated in Fig.2.

At each time period, we formulate a bargaining game to address the time sharing problem. For the \( T^I \) period, the idle time bargaining game \( (\mathcal{G}_I^G) \) is designed. In the \( \mathcal{G}_I^G \), individual STs in the \( \mathcal{D} \) are game players, and the \( T^I \) period is shared through the concept of the MNBS to actively transmit the STs’ data. When the primary channel is busy, the \( T^B \) period is evenly shared by STs. Each time slot, which is assigned for each ST, is divided for the energy harvest and backscatter modes. For the \( \tau_i \) division problem, the busy time bargaining game \( (\mathcal{G}_B^G) \) is formulated, and the \( \tau_i \) is divided based on the idea of the ENBS. During the \( T^B \) period, multiple \( \mathcal{G}_{1 \leq i \leq n} \) games are operated in a parallel manner. Therefore, the \( \mathcal{G}_I^G \) and \( \mathcal{G}_B^G \) are repeated in a step-by-step manner, and the time sharing process is operated interactively at each time period. Formally, we define the \( \mathcal{G}_I^G \) and \( \mathcal{G}_B^G \) game entities, i.e, \( \mathcal{G} = \{\mathcal{G}_I^G, \mathcal{G}_B^G\} = \{\mathcal{P}_T, S_G, \mathcal{D}, \{\mathcal{G}_I^G | \mathcal{G}_{1 \leq i \leq n}\}, \mathcal{U}_{1 \leq i \leq n} \} \), \( \{\mathcal{G}_B^G | \tau_i, (n_i^{EH}, m_i^{BS}, \rho_i, (\underline{U}_i^{EH}, \underline{U}_i^{BS}))\}, T \} \) of gameplay.

- The \( \mathcal{G}_I^G \) and \( \mathcal{G}_B^G \) are mutually and reciprocally interdependent in an interactive manner, and they work together to share each limited time resource.
- \( \mathcal{P}_T \) is the PT, \( S_G \) is the SG, and \( \mathcal{D} \) is the set of STs in our backscatter-aided RF-powered CR system platform.
- In the \( \mathcal{G}_I^G \), \( \mathcal{G}_{1 \leq i \leq n} \in \mathcal{D} \) are the game players, \( \mathcal{X}_{1 \leq i \leq n} \) are their strategies, and \( \mathcal{U}_{1 \leq i \leq n} \) are their utility functions.
- In the \( \mathcal{G}_B^G \), \( \tau_i \) is the time slot assigned for the \( D_i \); it is divided by the time splitting ratio \( \rho_i \) where \( 0 \leq \rho_i \leq 1 \).
- \( n_i^{EH} \) is the energy harvest mode and \( m_i^{BS} \) is the backscatter mode. They are game players in the \( \mathcal{G}_B^G \), and the \( \rho_i \) is the strategy. The \( \underline{U}_i^{EH} \) and \( \underline{U}_i^{BS} \) are utility functions of \( n_i^{EH} \) and \( m_i^{BS} \), respectively.
- Discrete time model \( T \in \{t_1, \ldots, t_c, t_{c+1}, \ldots\} \) is represented by a sequence of time steps. The \( t_c \) can be the \( T^I \) or \( T^B \), and the length of \( t_c \) matches the event time-scale of \( \mathcal{G}_I^G \) or \( \mathcal{G}_B^G \).

B. THE BASIC IDEAS AND CONCEPTS OF THE ENBS AND MNBS

To characterize the basic ideas of the ENBS and MNBS, we first start with some definitions. Let \( N = \{1, \ldots, n\} \) be the set of players with \( n \geq 2 \). Let \( R^+_n \) be the set of all nonnegative real numbers, and denote \( R^+_n \) be the \( n \)-fold Cartesian product of \( R^+ \). For any \( x, y \in R^+_n \) and for all \( i \in N \), we write \( x \geq y \) to mean \( x_i \geq y_i \), \( x \succ y \) to mean \( x_i \geq y_i \) and \( x \neq y \), \( x \gg y \) to mean \( x_i > y_i \). Let \( \sum \) be the set of all subsets of \( R^+_n \).
and elements in \( \sum \) are interpreted as bargaining problems. For every bargaining problem \( A \in \sum \), a bargaining solution \( F \) assigns a nonempty subset \( F(A) \) of \( A \). For all \( A \in \sum \) and all \( i \in N \), let \( M_i(A) = \max \{ a_i | (a_1, \ldots, a_i, \ldots, a_n) \in A \} \). \( M(A) = (M_i(A))_{i \in N} \) is the ideal point of \( A \). The classical Nash bargaining solution (NBS) over \( \sum \) is mathematically defined as follows [10]:

\[
\text{NBS} (A) = \max_{a \in A} \prod_{i \in N} a_i, \quad \text{s.t., all } A \in \sum
\]

Several axioms - Efficiency, Anonymity, Scale Invariance, and Weak Contraction Independence - are standard in the literature on Nash bargaining problems. All the points in the NBS(A) lie on the highest indifference surface given by \( \min \left( \frac{a_1}{M_1(A)}, \ldots, \frac{a_n}{M_n(A)} \right) \) attainable in \( A \) where \( a \in A \). According to (1), the NBS can be rewritten as follows [10]:

\[
\text{NBS} (A) = \left\{ a \in A | \min_{i \in N} \left( \frac{a_i}{M_i(A)} \right) \geq \min \left( \frac{x_1}{M_1(A)}, \ldots, \frac{x_n}{M_n(A)} \right), \forall x \in A \right\}
\]

s.t., all \( A \in \sum \) \hspace{1cm} (2)

As a refinement of the classical NBS, the ENBS over \( \sum \) is defined by considering the concept of egalitarianism. Therefore, the ENBS satisfies all standard axioms for the NBS while additionally ensure the axiom of Equity Principle. Formally, the ENBS is given as follows [10]:

\[
\text{ENBS} (A) = \left\{ a \in \text{NBS} (A) | \min_{i \in N} \left( \frac{a_i}{M_i(A)} \right) \geq \min_{i \in N} \left( \frac{x_i}{M_i(A)} \right), \forall x \in \text{NBS} (A) \right\}
\]

s.t., all \( A \in \sum \) \hspace{1cm} (3)

Another bargaining solution, called the MNBS, is designed from a different standpoint. The conventional NBS results in equal surpluses for all players. However, the MNBS is proposed to provide a fair bargaining solution, in which players who pay more for investments would receive higher surpluses. It is more motivating for the participating players. To do this, the original Nash solution is modified and the MNBS is defined as follows [9]:

\[
\text{MNBS} = \left\{ a \in A | \min_{i \in N} \left( \frac{\sum_{i=1}^{n} a_i}{n} \right) \geq \min_{i \in N} \left( \frac{\sum_{i=1}^{n} x_i}{n} \right) \right\} \quad \text{for all } x \in A
\]

s.t., \( \sum_{i=1}^{n} f(a_i) \) and \( \sum_{i=1}^{n} f(x_i) \) \hspace{1cm} (4)

where \( f(\cdot) \) is the reward function for the \( i \)'s investment. According to (4), the MNBS can be rewritten as follows:

\[
\text{MNBS} = \max_{a \in A} \left( \prod_{i \in N} a_i \right), \quad \text{s.t., } \sum_{i=1}^{n} f(x_i) = n
\]

\[
\text{C. THE DUAL BARGAINING GAME IN THE RF-CR PLATFORM}
\]

To develop a new dual bargaining game model, we construct the \( G^I \) and \( G^R \) games by relying on the influence of reciprocal interaction. For the \( T^I \) period, the \( G^I \) is designed to share the limited time resource among the STs. As a game player, the \( D_i \) select their strategy \( x_i \) by considering not only its generated data amount, but also its current energy level. At the time \( t \), the \( D_i \)'s utility function, that is, \( U_{D_i}^I(\cdot) \), is defined as follows:

\[
U_{D_i}^I(x_i, \mathcal{E}_D^I, \mathcal{E}_G^D, \mathcal{M}_D) = \left( \min \left( \chi_{D_i}, \mathcal{E}_T^I \right) - \mathcal{T}_D^I \right) \frac{\beta^\mathcal{T}_D^I}{\mathcal{T}_D^I} \left( \frac{\mathcal{E}_D^I - \mathcal{E}_G^D}{\mathcal{E}_D^I} \right)
\]

s.t., \( \mathcal{T}_D^I \geq 0 \) \hspace{1cm} (5)

\[
\text{where } \mathcal{E}_T^I \text{ is the total communication capacity of } T^I \text{ period, and } \mathcal{E}_D^I \text{ is the generated data amount of } D_i, \mathcal{E}_G^D \text{ is the full energy capacity of } D_i, \mathcal{E}_D^I \text{ is the } D_i \text{'s energy status at time } t. \text{ } \beta \text{ and } \varphi \text{ are control parameters for } U_{D_i}^I(\cdot) \text{. In the } G^I, \text{ multiple ST devices, that is, } D_{i \leq i \leq n}, \text{ are assumed as game players, and they share the } T^I \text{ period in a fair-efficient way. To implement this sharing process, we should consider each player’s contribution for the social welfare. Usually, spectrum sensing is the ground work for the realization of CR technology. In this study, the cooperative spectrum sensing method has been presented as an effective sensing way to improve the performance of sensing in the CR system. The main idea of cooperative sensing is to enhance the sensing performance if a group of SUs voluntarily contribute to sensing and share their local sensing information to get a better picture of the spectrum usage. For making a combined decision, which is more accurate than the individual decisions, spectrum sensing information are collected at the S_G. Then, the S_G decides whether any primary user is active or not. However, STs are intuitively reluctant to cooperatively sense and would prefer to free-ride without contributing anything. It is the well-known free-ride problem [13].}

To avoid the ST's free-ride problem, we should consider the each ST's contribution in the \( G^I \) game process. Therefore, in this study, we adopt the concept of MNBS for the \( G^I \) game. According to (4)-(6), the MNBS is obtained as follows:

\[
\text{MNBS} (x_{1 \leq i \leq n} | \mathcal{D}) = \max_x \left( \mathcal{H}_D (x) \cdot \prod_{D_i \in \mathcal{D}} U_{D_i}^I(x_i, \mathcal{E}_T^I, \mathcal{E}_D^I, \mathcal{E}_G^D, \mathcal{M}_D) \right)
\]
For the $ρ$ game players, and the decision of
perspective and parallel manner. In the
where $\eta$ and $θ$ are common control parameters for $U_i (\cdot)$. $μ$ is a modification factor for $U_i^{BS} (\cdot)$ and $σ$, $ζ$ are modification factors for $U_i^{EH} (\cdot)$. In the $D_i$’s point of view, the equity principle should be considered for the $m_i^{BS}$ and $m_i^{EH}$. Therefore, the idea of $ENBS$ is chosen for the $G_i^B$ game. According to (3) and (8), the $ENBS$ is obtained as follows:

$ENBS \left( \left( U_i^{BS} (\cdot), U_i^{EH} (\cdot) \right) \mid ρ_i \right) = \min \left\{ \frac{U_i^{BS} (\cdot) \mid ρ_i}{M_i^{BS}}, \frac{U_i^{EH} (\cdot) \mid 1 - ρ_i}{M_i^{EH}} \right\}$

s.t., $\left( U_i^{BS} (\cdot), U_i^{EH} (\cdot) \right) \mid ρ_i$, $\left( U_i^{BS} (\cdot), U_i^{EH} (\cdot) \right) \mid ρ_i'$

$∈ NBS \left( U_i^{BS} (\cdot), U_i^{EH} (\cdot) \right)$

$D. MAIN STEPS OF OUR RF-CR SYSTEM TIME SCHEDULING ALGORITHM$

In this paper, we propose two different bargaining games, i.e., $G_i^B$ and $G_i^I$, to address the time sharing problem in a backscatter-aided RF-CR infrastructure. Based on the concepts of the $ENBS$ and $MNBS$, we formulate a novel dual bargaining model to obtain an fair-efficient solution while maximizing the system throughput. According to the $ENBS$, each $ST$ dynamically switches between HTT and backscatter modes. Based on the $MNBS$, the $S_G$ distributes the time slots for individual $ST$s, and they are used for the active data transmission of $ST$s. During the $T^B$ and $T^I$ periods, the $G_i^B$ and $G_i^I$ games are operated repeatedly in a step-by-step interactive online manner. Due to the desirable characteristics of the $ENBS$ and $MNBS$, we can maximize the RF-CR system throughput, normalized ST payoff and ST fairness while effectively ensuring the trade-off among conflicting control issues. Usually, control algorithms have exponential time complexity in order to solve classical optimal problems. However, in this study, we do not focus on trying to get an optimal solution based on the traditional optimal approach. But instead, the $ENBS$ and $MNBS$ in our dual-bargaining game model are obtained with polynomial complexity. The main steps of our proposed algorithm can be described as follows:

$Step 1$: To implement our proposed time scheduling algorithm for the backscatter-aided RF-CR platform, the values of the adjustment parameters and control factors are listed in Table 1, and the simulation setup is given in Section IV.

$Step 2$: At each time epoch $t$, multiple $ST$ devices generate their task services in the IoT paradigm.

$Step 3$: During the $T^I$ period, the $G_i^I$ game is operated on the $S_G$, the $D_{i,t} \leq n$ are game players, and their utility functions $(U_{D_{i,t}} (\cdot))$ are defined according to (6).

$Step 4$: For the $G_i^B$ game, the concept of the $MNBS$ is adopted, and the $x_{i,t} \leq n$ values are determined using (7).

$Step 5$: During the $T^B$ period, multiple $G_i^B$ games are operated in a dispersive and parallel manner. In the $G_i^B$ of $D_i$, the $m_i^{BS}$ and $m_i^{EH}$ are game players, and their utility functions $(U_i^{BS} (\cdot), U_i^{EH} (\cdot))$ are defined according to (8).

$Step 6$: For the $G_i^B$ game, the idea of the $ENBS$ is chosen, and the $x_{i,t} \leq n$ values are determined using (9).

$Step 7$: During the $T^B$ and $T^I$ periods, the sequential interaction of $G_i^B, G_i^B, G_i^I$ games are explored to achieve mutual advantages. Based on an integrated dual bargaining game model, network agents work together to achieve an optimal performance in a coordinated manner.

$Step 8$: Constantly, individual game entities self-monitor the current RF-CR network environments, and proceed to Step 2 for the next dual bargaining game process.
TABLE 1. System parameters used in the simulation experiments.

| Parameter | Value | Description |
|-----------|-------|-------------|
| \( \eta \) | 5 | the total number of ST devices |
| \( \beta, \theta \) | 2, 0.5 | control parameters for \( \text{U}_k^S () \) |
| \( \alpha, \gamma \) | 1, 1 | control parameters for \( \text{U}_k^T () \) |
| \( \eta, \theta \) | 1, 2 | common control parameters for \( \text{U}_k^T () \) |
| \( \mu \) | 0.3 | modification factor for the \( \text{U}_k^T () \) |
| \( \sigma, \xi \) | 3, 0.5 | modification factors for the \( \text{U}_k^T () \) |

| Task service types | Communication requirement | Service duration |
|--------------------|--------------------------|-----------------|
| I                  | 256 Kbps                 | 20 t            |
| II                 | 64 Kbps                  | 25 t            |
| III                | 32 Kbps                  | 30 t            |
| IV                 | 128 Kbps                 | 35 t            |
| V                  | 96 Kbps                  | 40 t            |
| VI                 | 192 Kbps                 | 15 t            |

**IV. PERFORMANCE EVALUATION**

In this section, simulation results are presented to evaluate the performance of the proposed time scheduling algorithm and the existing SDTS, WPBC and PBTF protocols in [6], [11], [12]. For the performance comparison, we adopt the simulation scenario and environment setup as follows:

- The simulated backscatter-aided RF-CR platform consists of one \( P_T \), one \( S_G \), and 5 ST devices where \( |D| = 5 \), ST devices are randomly located in the neighboring area of \( S_G \).
- Total communication capacity of each time period \( (T^I \text{ or } T^B) \) is 1 Gbps.
- Task services are generated in each individual ST device. At each time epoch, the generation process for task services is Poisson with rate \( \Lambda \) (services/t), and the range of offered workload was varied from 0 to 3.0.
- Six different task services are assumed based on their communication requirements and service duration times.
- The full energy capacity of \( D (E_D) \) is 10 gigajoule (GJ), and the energy consumption for one time slot data communication is assumed as one kilojoule (KJ).
- In each individual \( D \), the selection of \( \Upsilon \) or \( \Phi \) is decided rationally based on the evolutionary learning mechanism.
- The number of time slots in the \( T^I \) period 100. Therefore, one time slot capacity 10 Mbps.
- System performance measures obtained on the basis of 100 simulation runs are plotted as a function of the offered task request load.

Fig.3 plots the average system throughput using the proposed time scheduling scheme and using the SDTS, WPBC and PBTF protocols. As the service generation rate increases, total communication amount increases. With the increase of data communications, the system throughput also increases, which is intuitive. From the simulation results, it can be observed that the performance of the proposed scheme is superior to that of the other existing protocols, which indicates that our dual bargaining game approach can make control decisions adaptively under the dynamics of backscatter-aided RF-CR network environments. Based on a step-by-step interactive mechanism, our proposed data transmission policy can improve the system throughput from low to heavy workload intensities.

Fig.4 indicates the normalized payoff received by STs of all protocols. As shown in the resulting curves, we can observe that the proposed scheme maintains higher payoff outcomes for different task workload situations. When the workload load increases, it becomes more certain. This is because the ideas of the \text{ENBS} and \text{MNBS} are applied to each individual ST device to effectively share the constrained time resources. The simulation results clearly confirm that our dual bargaining approach can guarantee efficient properties in the time sharing problem in the RF-CR platform.

Fig.5 presents fairness comparisons. From the viewpoint of individual ST device, fairness is a desirable property in the RF-CR system operations. Traditionally, cooperative games and bargaining solutions are paradigmatic for certain fairness considerations. The major characteristic of our dual bargaining game model is also to provide a fair-efficient solution while ensuring the tradeoff among conflicting control issues. It leads to a preferable outcome in the fairness comparison.
Therefore, we can achieve the best fairness than the SDTS, WPBC and PBT$k$ protocols for the range of offered workload rates. The simulation results shown in Figs.3 to 5 demonstrate that the proposed scheme can strike an appropriate performance balance under widely diversified task workload situations.

V. SUMMARY AND CONCLUSION
In this paper, we investigate a time sharing problem for the backscatter-aided RF-CR platform by incorporating the concept of cooperative game theory. First, a comprehensive network infrastructure is presented with intelligent and rational system agents. Then, we explain the basic ideas of the ENBS and MNBS to design a novel dual bargaining game. These two solutions are important how to effectively decide control decisions under dynamically changing RF-CR system environments. To strike an appropriate performance, the $G^I$ and $G^B$ games work together interactively in a cooperative manner while ensuring good global properties. During the step-by-step game iteration, our proposed approach is adaptively responsive to the current system conditions. Finally, simulation experiments demonstrate that our proposed scheme has advantages in terms of system throughput, ST payoff and fairness than the existing SDTS, WPBC and PBT$k$ protocols. It is worth noting that the proposed dual bargaining game model is able to efficiently utilize the limited time resources while contributing to improve the RF-CR system performance.

Research on the time sharing problem in a backscatter-aided RF-CR platform is still in its infancy. An interesting continuation of our study presented in the study can be extended in a number of ways. One future direction is to consider a non-orthogonal-multiple-access (NOMA) technique for the bi-static backscatter communication network. Another potential direction for future research is to investigate and analyze a two-user single decode-and-forward (DF) relay network with ambient backscatter communication capabilities. In addition, we will develop a RF-powered underlay cognitive radio system with machine learning (ML) algorithms.

COMPETING OF 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.

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