IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

SPECIAL SECTION ON WIRELESSLY POWERED NETWORKS ALGORITHMS, APPLICATIONS AND TECHNOLOGIES

Received August 31, 2018, accepted September 16, 2018, date of publication September 24, 2018, date of current version October 17, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2872024

Full-Duplex Wireless Powered IoT Networks

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ABSTRACT This paper studies the emerging wireless power transfer for the Internet-of-Things (IoT) network, where one hybrid access point (H-AP) with constant power supply communicates with a set of IoT devices. This H-AP is assumed to work in a full-duplex mode, which transmits/receives signals to/from these IoT devices simultaneously during the whole frame. The IoT devices are capable of harvesting energy from the received signals broadcast by the H-AP. And the harvested energy is used to support the uplink transmission. Since time-division multiple access is used in uplink transmission, one IoT device keeps harvesting energy till its own uplink time slot. The objective of this paper is to maximize the total surplus energy, which is defined as the gap between available energy and consumed energy for uplink transmissions, by exploiting the optimal time allocation scheme for each device. A distributed non-cooperative and a bargaining cooperative game-based algorithms are proposed to solve this problem. In addition, the well-known KKT condition approach is adopted as a comparison. The numerical results show that the bargaining cooperative algorithm outperforms the distributed non-cooperative algorithm (DNCA) and KKT algorithm (KKTA) in terms of total surplus energy and fairness index. The performance of DNCA is better than that of KKTA in terms of total surplus energy while KKTA is fairer than DNCA.

INDEX TERMS Wireless power transfer, full-duplex, Internet-of-Things, game theory, surplus energy, fairness index.

I. INTRODUCTION

5G era is characterized by its high density of base stations and terminals [1]. It is widely reported that the 5G network has to accommodate more than 1 trillion devices including IoT terminals and human-oriented terminals [2]. Many challenges are coming together with this significant evolution of wireless communication technology, e.g., resource management issues, radio access issues, and energy consumption issues, etc. Due to the limitation of battery and power supply of IoT networks, energy consumption issues have attracted many researchers working on this topic. Many innovative protocols and algorithms are proposed to address these problems from different aspects.

The development of renewable energy such as solar, wind and tide has lasted for many years. Currently, these renewable energy sources have been an irreplaceable part of the power supply. However, applying renewable energy techniques to wireless communication networks is a relatively new idea. Compared with conventional grid power supply, renewable energy is more environmental friendly and sustainable. Reference [3] considers a communication system powered by both grid and renewable energy sources and the grid energy price is minimized by the proposed optimization algorithm. Hu *et al.* [4] propose a capacity maximization algorithm based on a MIMO system powered by smart grid as well as renewable energy sources. A novel spectrum and energy cooperation strategy are proposed in [5]. Reference [6] investigates the traffic load balancing in backhaul-constrained cache-enabled small cell networks powered by hybrid energy sources.

However, the availability of these renewable energy sources is extremely limited by the environment (i.e., no solar at night). In this case, harvesting energy from ambient radio signals has been a more reliable and available alternative for the energy-sensitive terminals, such as wearable devices. Reference [7] has demonstrated that $3.5mW$ and $1\mu W$ can be harvested from 0.6 and 11 meters away. Mikeka and Arai [8] show that over 50% harvesting efficiency can be achieved with $-5dBm$ input power. In addition to harvesting energy, the normal data transmission is able to be conducted simultaneously, which is called simultaneous wireless information and power transfer (SWIPT) [9]. This novel technique requires a unique receiver architecture where the received signal is split either in the time domain or power domain [10]. However, challenges still puzzle researchers and engineers regarding hardware design [10], modulation and coding scheme selection [11] and security issues [12]. In this paper, we consider a full duplex IoT network where the terminals are powered by RF energy harvesting.

A. RELATED WORKS

Wireless charging technology is originally proposed with resonant inductive coupling and magnetic resonance coupling. But the features of these two techniques (i.e., low effective distance and low charging efficiency) greatly limit their deployments and applications [10]. Then, radio frequency energy transfer or wireless energy transfer (WET) is proposed, which overcomes these two problems. Therefore, we only focus on WET in this paper.

Huang and Lau [13]authors propose a novel frame that enables wireless power transfer in cellular networks in terms of network architecture, modeling as well as the deployment of power beacons. Reference [14] considers a medium access control protocol for wireless sensor networks which is powered by WET. The average network throughput is improved by 112% over a modified unslotted CSMA MAC protocol. Reference [15] considers a typical WET scenario where all users harvest energy from downlink and exhaust their harvested energy to uplink transmission by time-division-multiple-access (TDMA). The corresponding throughput is maximized by the proposed algorithm. The similar network architecture is applied in [16] where the minimum user throughput is maximized by a joint design of the DL-UL time allocation, the DL energy beamforming, and the UL transmit power allocation, as well as receive beamforming. Reference [17] maximizes the sum rate via the power control optimization in a two user network with interference channel where time switch structure is applied. Ju and Zhang [18] consider a full-duplex wireless powered communication network (FD-WPCN) where one hybrid access point (H-AP) broadcasts wireless energy to users in the downlink meanwhile receives information from the users by TDMA in the uplink. An efficient protocol that supports this two-way communication is designed to maximize the weighted sum uplink rate of all users. Reference [19] addresses the impact of massive MIMO on the user association in massive multiple-input multiple-output (MIMO)-aided heterogeneous networks (HetNets) embedded wireless power transfer (WPT).

Game theory has been widely applied in wireless communication. It provides analytical tools to predict the outcome of complex interactions among rational entities [20]. The advantages of game theory make it be used as an efficient approach to solve resource allocation problems. In general, game theory consists of the non-cooperative game model and cooperative game model. In [21], a non-cooperative game model in terms of uplink power control is formulated with the objective of maximizing its own utility. A Pareto optimal solution is obtained for the formulated game model. The non-cooperative game model is also used in [22]–[24] to maximize their prescribed utility functions in different network scenarios via optimal power control. Besides, joint resource allocation problems also can be solved by non-cooperative game model. Reference [25] models the resource allocation problem as a non-cooperative game with self-interested players and objective of maximizing its own energy efficiency in interference-limited device-to-device communication networks. Reference [26] proposes a supermodular game model where the utility function is designed by considering both transmission power and rate. The derived distributed algorithm reaches the expected Nash Equilibrium (NE) through an iterative manner. In [27], A big data-integrated coalition game approach is adopted to achieve dependable content distribution in D2D cooperative vehicular networks. And bandwidth allocation and admission control algorithms are obtained on basis of this cooperative game model. Reference [28] considers a relay network where the signals transmitted from source to destiny is forwarded by the relay. A bargaining game is formulated to determine the power allocation to the relay and users. The Nash Bargaining Solution (NBS) is obtained and a balance between the sum-rate and the user fairness is achieved as well. A unified cooperative bargaining game is formulated in [29] where spectrum allocation, power allocation, and simultaneous multiresource allocation are taken into consideration. A good trade-off between computational complexity and system efficiency is achieved via the derived NBS.

In order to solve the issues of wireless energy transmission, game theory has been considered as an efficient methodology to address the formulated problems in various network setups. Reference [30] considers a multiple source-destination network with objectives to minimize their own transmission power under the constraints of SINR and energy harvesting with the non-cooperative game theory. A stackelberg game is formulated in [31] with a power beacon-assisted wireless-powered communication network, where the proposed algorithm achieves better performance in terms of per unit throughput. Zheng *et al.* [32] adopt the time switching-based relaying (TSR) protocol in a half-duplex relay network, where the whole frame of the relay is dynamically divided into three parts: energy harvesting, data transmission from sources to the relay and data transmission from relay to destinations. The Nash bargaining approach is used to balance the information transmission efficiency of source-destination pairs and the harvested energy of the relay. In addition, [33] tries to maximize the energy efficiency via minimizing the total consumed energy in a clustering IoT network with energy harvesting. An iteration-based IPCTA algorithm for TDMA is proposed to minimize the total energy consumption.

Different from the above papers, this paper considers a full duplex H-AP which transmits energy to the devices and receives information from the devices simultaneously with TDMA. In order to give a direct insight into the behavior of each individual device under the different game model, the non-cooperative game theory and cooperative game theory are applied to address the issue of surplus energy maximization, respectively. In addition to focusing on the energy issue, the fairness problem is also considered in this paper. And the numerical results show the superiority of our proposed algorithms in terms of both surplus energy and fairness.

B. CONTRIBUTIONS

The main features of the IoT network in 5G are summarized as large quantities of intelligent terminals, long lifetime and small traffic volume [34]. Therefore, in order to enhance the lifetime of the massive IoT devices, this paper adopts the wireless power transfer technique which is regarded as a reliable option to charge the massive IoT devices. Furthermore, since the lifetime of an IoT device is critical and mainly determined by the available energy, the objective of this paper is to maximize the surplus energy by exploring the optimal time allocation scheme under the constraint of data volume for each individual IoT device. The main contributions of this paper are summarized as follows:

- Rather than throughput maximization and energy efficiency optimization in most related papers, we consider surplus energy maximization in this paper because the battery capacity is very limited for most IoT devices. And it is also inconvenient and uneconomical to frequently recharge these mass deployed IoT devices. To some extent, the surplus energy indicates the reliability and availability of an IoT device, which is quite important for some practical use cases like industrial IoT networks and environment monitoring IoT networks.
- Different from the papers using half-duplex mode, the proposed network setup in this paper consists of an H-AP in the full-duplex mode which extremely improves the energy harvesting efficiency and a set of IoT devices enabling energy harvesting with TDMA which eliminates the uplink mutual interference among the IoT devices.
- The nature of game theory empowers the IoT devices with intelligence, which means every individual device is considered as a rational player who is capable of making decisions based on its own acquired information and rules. This feature matches the formulated problem in this paper, where the time allocation of each device is mutually affected.
- Different from the papers using game theory, we use both non-cooperative game theory and cooperative game theory to solve this surplus energy maximization problem. The diverse game-based approaches give an insight into this optimization problem. The developed distributed non-cooperative algorithm allows each individual device to make selfish decisions without exchanging any information among the devices, which simplifies the system complexity. On the contrary, the bargaining cooperative game requires full communications among the devices, which results in a better system performance.
- All theoretical analysis is verified by extensive numerical simulations. The proposed bargaining cooperative algorithm outperforms the other two by sacrificing the computational complexity. The performance of the proposed distributed non-cooperative algorithm is better than that of the KKT condition regarding the total surplus energy while the KKT condition is fairer than the proposed non-cooperative algorithm.

The rest of this paper is organized as follows: Section II shows the system model and the whole frame structure. Section III formulates the problem and derives the solutions based on the distributed non-cooperative game model and bargaining cooperative game model. The numerical results are presented in Section IV. Finally, this paper is concluded in Section V.

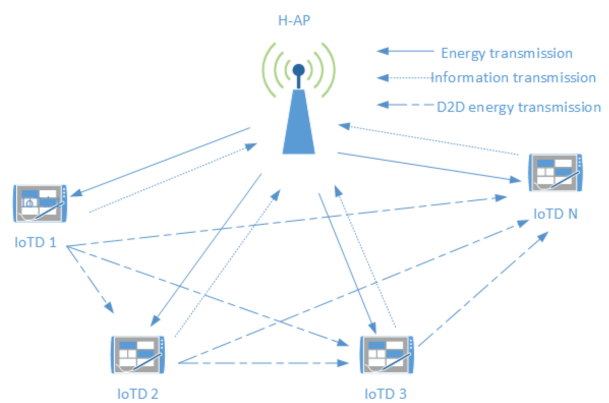

FIGURE 1. System model.

II. SYSTEM MODEL

As illustrated in Fig. 1, this paper considers a wireless powered IoT network consisting of one H-AP communicating with multiple IoT devices denoted by $IoTD_i$, $i = 1, \cdots, N$. It is assumed that the H-AP and all devices operate in full-duplex and half-duplex, respectively. Therefore, the H-AP is able to broadcast energy signal and receive information simultaneously. In the downlink direction, each device harvests energy from the received signal broadcast by the H-AP with practical non-linear energy harvesting model introduced in [35]. Since TDMA is adopted in uplink transmission, each individual IoT device keeps harvesting till its allocated time slot defined by $T\tau_i, i = 1, \cdots, N$, which is illustrated in Fig. 2. T is defined as the frame length and τ_i is a ratio varying from 0 and 1. Note that in order to ensure the initial operation of the IoT devices, an original available energy is defined as E_i^O and an initial energy harvesting time slot is defined as $T\tau_0$. The downlink, uplink, and interference channels are assumed to be quasi-static flat-fading with h_i, g_i and g_{ji}, respectively.

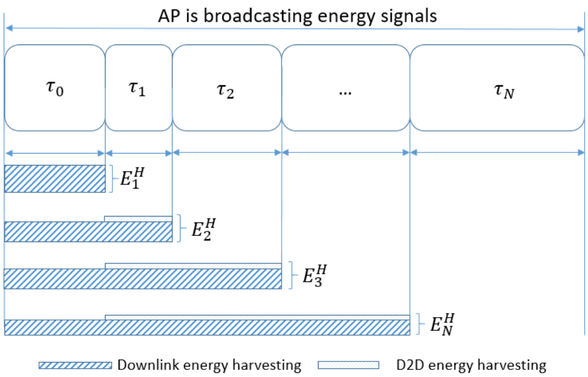

FIGURE 2. Time frame structure.

A. ENERGY HARVESTING MODEL

The H-AP broadcasts energy signal to all IoT devices during the whole frame and the uplink transmission of one device interferes with other devices which are harvesting energy. Hence, the signal received by the $IoTD_i$ is expressed as

$$y_i(\tau_j) = \sqrt{P_{AP}}h_i x + I_j(\tau_j) + n_i \tag{1}$$

where $I_j(\tau_j) = \sqrt{P_j} g_{ji} x_j, j = 0 \cdots i-1$. Note that $I_0(\tau_0) = 0$. P_{AP} is the transmission power of the H-AP. P_j is the uplink transmission power of $IoTD_j$ and x and x_j are the transmitted signals with $\mathbb{E}[|x|^2] = \mathbb{E}[|x_i|^2] = 1$. $n_i \sim \mathcal{CN}(0, \sigma_i^2)$ is the additive Gaussian noise introduced by the received antenna at the $IoTD_i$. Note that although the received signal of (1) consists of the interference from the uplink transmission device, the harvested energy from interference is neglectable because the interference power is pretty small compared with that from the downlink transmission and it is too small to trigger the energy harvesting functionality since there exists a receiver sensitivity threshold for the non-linear harvesting model. Therefore, the harvested energy of $IoTD_i$ during the whole frame is written as

$$E_i^H = \sum_{j=0}^{i-1} u(P_{AP}|h_i|^2) T \tau_j \tag{2}$$

where $u(\cdot)$ is defined as follows [35]

$$u(x) = \frac{M(1+e^{ab})}{e^{ab} + e^{-a(x-b)}} - \frac{M}{e^{ab}} \tag{3}$$

where a, b and M are positive parameters which capture the joint effects of different non-linear phenomena caused by hardware constraints. Therefore, the total available energy of $IoTD_i$ can be expressed as

$$E_i^A = E_i^O + E_i^H \tag{4}$$

B. ENERGY CONSUMPTION MODEL

In the allocated uplink time slot, $IoTD_i$ transmits data to the H-AP with achievable throughput

$$R_i = BT\tau_i ln(1 + \frac{P_i|g_i|^2}{\sigma_i^2}) \tag{5}$$

where B is the bandwidth. Different from many energy harvesting papers, the circuit power consumption is taken into account in this paper. It has been proved in [33] that the circuit power consumption makes a non-negligible impact on the system performance with energy harvesting. Thus, the consumed energy of $IoTD_i$ is written as

$$E_i^C = \tau_i T(P_i + P_c) \tag{6}$$

where P_i is the uplink transmission power of $IoTD_i$ and P_c is the uniform circuit power consumption of all devices.

C. SURPLUS ENERGY MODEL

Based on the previous discussions, the surplus energy of $IoTD_i$ is defined as

$$E_i^S(\boldsymbol{\tau}) = \begin{cases} E_i^A - E_i^C, & \text{if } E_i^A \geq E_i^C \text{ and } \sum_{j=0}^{i} \tau_j \leq 1 \\ E_i^A, & \text{else} \end{cases} \tag{7}$$

where $\boldsymbol{\tau} = [\tau_1, \cdots, \tau_N]^T$ denotes the time allocation ratio vector for all IoT devices. This definition of surplus energy indicates that it is possible that some of the devices do not have the opportunities to conduct uplink transmission due to insufficient harvested energy and limited frame length. Once the available energy is less than the consumed energy or its allocated slot exceeds the frame length, the corresponding device does nothing but harvest energy. This mechanism ensures most devices are able to implement uplink transmission after energy harvesting meanwhile provides an opportunity to those who experience an insufficient energy harvesting to accumulate more energy for the next frame. Note that for the long-term cases with multiple frames, a well-designed scheduling scheme is needed to achieve a long-term optimal system performance, which is not within the scope of this paper but a possible direction of our future research.

III. GAME THEORETICAL ALGORITHM

The system performance is characterized by the total surplus energy. Naturally, the global optimization problem can be formulated as

$$\max_{\boldsymbol{\tau}, R_i} \sum_{i=1}^{N} E_i^S(\boldsymbol{\tau}) \tag{8}$$

Constraints:

$$0 < \tau_i < 1 \tag{9}$$

$$0 < \sum_{i=0}^{N} \tau_i < 1 \tag{10}$$

$$R_i \geq D_i \tag{11}$$

$$0 < P_i \leq P_{max} \tag{12}$$

where D_i is denoted as the required data volume of uplink transmission of $IoTD_i$ and P_{max} is the maximum transmission power of each device. To solve this global optimization problem, we develop a distributed non-cooperative game based algorithm and a bargaining cooperative game based algorithm.

A. DISTRIBUTED NON-COOPERATIVE GAME BASED ALGORITHM

The distributed non-cooperative method allows each device to make its individual decision without exchanging any decision information with other devices. Accordingly, the global optimization degenerates into a local optimization problem of $IoTD_i$, which can be expressed as

$$\max_{\boldsymbol{\tau},R_i} E_i^S(\boldsymbol{\tau}) \tag{13}$$

Constraints: (9), (11) and (12).

Note that since no decision information is exchanged in this distributed non-cooperative method, (10) is meaningless for each individual device, which characterizes the distributed non-cooperative method. In addition, it is clear that (11) has to hold equality in this local maximum problem. Therefore, the uplink transmission power is derived as

$$P_i = \frac{\sigma_i^2}{|g_i|^2}\left(e^{\frac{D_i}{BT\tau_i}} - 1\right) \tag{14}$$

Substituting (14) into (6), we obtain

$$E_i^C = \tau_i\left(\frac{\sigma_i^2}{|g_i|^2}\left(e^{\frac{D_i}{BT\tau_i}} - 1\right) + P_c\right) \tag{15}$$

Therefore, this distributed non-cooperative game model can be represented as

- *Players*: N IoT players.
- *Actions*: uplink transmission time ratio determined by each individual IoT device.
- *Utilities*: the surplus energy defined in (7).

This game can be denoted as

$$\mathbb{G}_{DNC} = \langle N, \{\mathcal{A}_i\}, \{E_i^S(\boldsymbol{\tau})\}\rangle \tag{16}$$

where $\mathcal{A}_i$ is the feasible set of τ_i. In the following subsections, the proof of existence and uniqueness of the solution for this formulated game are provided.

1) EXISTENCE OF NASH EQUILIBRIUM

Nash Equilibrium (NE) is the solution to a non-cooperative game and it is defined that no player is able to increase its utility by deviating from the Nash Equilibrium [36]. For the formulated game $\mathbb{G}_{DNC}$, the NE satisfies the following inequality,

$$E_i^s\left(\tau_i^*, \boldsymbol{\tau}_{-\boldsymbol{i}}^*\right) \geq E_i^s\left(\tau_i, \boldsymbol{\tau}_{-\boldsymbol{i}}^*\right), \quad \forall \tau_i \in \mathcal{A}_i \tag{17}$$

where $\boldsymbol{\tau}_{-\boldsymbol{i}} = [\tau_1.\cdots, \tau_{i-1}, \tau_{i+1}, \cdots, \tau_N]^T$. The following theorem proposed in [37] is adopted to prove the existence.

Theorem 1: A NE exists in a non-cooperative game $\langle N, \{\mathcal{A}_i\}, \{u_i(\boldsymbol{X})\}\rangle$ if $\forall i \in N$, $\{\mathcal{A}_i\}$ is a *compact* and *convex* set. $u_i(\boldsymbol{X})$ is continuous in $\boldsymbol{X}$ and *quasi-concave* in x_i, where $\boldsymbol{X} = (x_i, \boldsymbol{X}_{-i})$.

After checking the properties of the action sets $\mathcal{A}_i$ and utility function $E_i^s(\boldsymbol{\tau})$, we have the following proposition in terms of NE existence:

Proposition 1: The action sets $\mathcal{A}_i$ are all compact and convex. The utility function $E_i^s(\boldsymbol{\tau})$ is quasi-concave in τ_i, $\forall i \in N$.

Proof: According to the definition of convex set [38] and compact set [39], $\mathcal{A}_i$ is both convex and compact and the utility function $E_i^s(\boldsymbol{\tau})$ is continuous in τ_i. And the quasi-concavity can be proved by the second partial derivative of the utility function with respect to τ_i, which is derived as

$$\frac{\partial E_i^s(\boldsymbol{\tau})}{\partial \tau_i} = -T\frac{\sigma_i^2}{|g_i|^2}e^{\frac{D_i}{BT\tau_i}}\left(1 - \frac{D_i}{BT\tau_i}\right) + T\frac{\sigma_i^2}{|g_i|^2} - TP_c \tag{18}$$

$$\frac{\partial^2 E_i^s(\boldsymbol{\tau})}{\partial \tau_i^2} = -\frac{1}{T\tau_i^3}\frac{\sigma_i^2 D_i^2}{|g_i|^2 B^2}e^{\frac{D_i}{BT\tau_i}} \tag{19}$$

It can be observed that the second partial derivative is negative, which indicates that the utility function $E_i^s(\boldsymbol{\tau})$ is quasi-concave with respect to τ_i.

Based on the above proof, it can be concluded that the formulated game $\mathbb{G}_{DNC}$ possesses at least one NE.

2) UNIQUENESS OF NASH EQUILIBRIUM

First of all, the iterative function for each device is derived by letting $\frac{\partial E_i^s(\boldsymbol{\tau})}{\partial \tau_i} = 0$. Thus, we obtain

$$\tau_i^{(t+1)} = \frac{X_i e^{\frac{X_i}{\tau_i^{(t)}}}}{e^{\frac{X_i}{\tau_i^{(t)}}} - Y_i} \tag{20}$$

where $X_i = \frac{D_i}{TB}$ and $Y_i = 1 - \frac{|g_i|^2}{\sigma_i^2}P_c$. Then we define the best response function $\mathcal{BR}(\tau_i^{(t)}) = \tau_i^{(t+1)}$. Hence, the best response vector function is written as $\boldsymbol{\mathcal{BR}}(\boldsymbol{\tau}) = [\mathcal{BR}(\tau_1), \cdots, \mathcal{BR}(\tau_N)]$. According to the fix point theorem [40], the action set $\boldsymbol{\tau}^*$ is a NE of the formulated game $\mathbb{G}_{DNC}$ if and only if it is the fixed point of $\boldsymbol{\mathcal{BR}}(\boldsymbol{\tau})$. Therefore, proving the uniqueness of NE for the formulated game $\mathbb{G}_{DNC}$ is equivalent to prove the uniqueness of the fixed point of function $\boldsymbol{\mathcal{BR}}(\boldsymbol{\tau})$. Furthermore, according to [41], the fixed point of $\boldsymbol{\mathcal{BR}}(\boldsymbol{\tau})$ is unique if $\boldsymbol{\mathcal{BR}}(\boldsymbol{\tau})$ is a *standard* function, which is defined as follows:

Definition 1: A function $f(x)$ is a *standard* function if the following properties are satisfied for all $x \geq 0$:

- *Monotonicity*: If $x \geq x'$, then $f(x) \geq f(x')$.
- *Scalability*: $\alpha f(x) > f(\alpha x)$, $\forall \alpha > 1$.

According to this definition, the following proposition is concluded.

Proposition 2: There exists a unique NE in the formulated non-cooperative game $\mathbb{G}_{DNC}$.

Proof: It is very straightforward to observe that $\mathcal{BR}(\tau_i)$ increases with the increase of τ_i. Then, we rewrite $\mathcal{BR}(\tau)$ as

$$f(\tau) = \mathcal{BR}(\tau) = \frac{X}{1 - \frac{Y}{e^{\frac{X}{\tau}}}} \tag{21}$$

therefore, we have $\alpha f(\tau) = X\frac{\alpha}{1-\frac{Y}{e^{\frac{X}{\tau}}}}$ and $f(\alpha\tau) = X\frac{1}{1-\frac{Y}{e^{\frac{X}{\alpha\tau}}}}$. Since $\alpha > 1$, we have

$$\lim_{\alpha\to 1} \alpha f(\tau) = \lim_{\alpha\to 1} f(\alpha\tau) \tag{22}$$

$$\lim_{\alpha\to+\infty} \alpha f(\tau) = +\infty \tag{23}$$

$$\lim_{\alpha\to+\infty} f(\alpha\tau) = \frac{X}{1-Y} \tag{24}$$

$$\frac{\partial \alpha f(\tau)}{\partial\alpha} > \frac{\partial f(\alpha\tau)}{\partial\alpha} \tag{25}$$

Based on the above analysis, we can conclude that there exists a unique NE in the formulated game $\mathbb{G}_{DNC}$.

3) DISTRIBUTED NON-COOPERATIVE ALGORITHM

In this subsection, an iterative and distributed time allocation algorithm is proposed in Algorithm 1. According to this algorithm, one IoT device is capable of achieving the NE point by updating its own decision to the convergence iteratively and independently. The achieved NE is actually the sub-optimal solution to the formulated problem (8).

Algorithm 1 Distributed Non-cooperative Algorithm

```
1: set bandwidth B, traffic volume D_i, circuit power consumption P_c, frame length T and iteration index t;
2: for t = t + 1 do
3:     calculate BR(τ_i^(t));
4:     if BR(τ_i^(t+1)) − BR(τ_i^(t)) ≤ ϵ then
5:         Output: τ_i
6:     end if
7: end for
```

B. BARGAINING COOPERATIVE GAME BASED ALGORITHM

The bargaining cooperative method requires sufficient negotiation before the players make decisions. Each player $IoTD_i$ has a utility function which is defined as U_i over the space $\{\mathcal{A}_i\}\bigcup\{D\}$, where D is the outcome if the players fail to reach an agreement, i.e., the disagreement outcome [42]. And the set of all potential utilities that these players is able to achieve is denoted as

$$\mathcal{S} = \{(U_1(\boldsymbol{\tau}), \cdots, U_N(\boldsymbol{\tau}))\,|\,\boldsymbol{\tau} = (\tau_1, \cdots, \tau_N) \in \mathcal{T}\} \tag{26}$$

Furthermore, the disagreement point is defined as $d = (d_1, \cdots, d_N)$ with $d_i = U_i(D)$. Therefore, a *bargaining problem* can be defined as

$$\mathbb{G}_{BC} = (\mathcal{S}, d) \tag{27}$$

where $\mathcal{S} \subset \mathbb{R}^N$ and $d \in \mathcal{S}$. For a cooperative game, Nash proposed *Nash axioms* ensuring the Nash Bargaining Solutions (NBSs) [43] which is originally dedicated for two-player cases. Since there are multiple devices in the system, the *extended Nash Theorem* is adopted.

Theorem 2: A Nash Bargaining Solution can be obtained by maximizing a Nash product term as

$$\max_{U_i\in\mathcal{S}, U_i\geq d_i, \forall i} \prod_{i=1}^{N} (U_i(\boldsymbol{\tau}) - d_i(\boldsymbol{\tau})) \tag{28}$$

Constraints: (9), (10), (11) and (12).

In order to solve this Nash bargaining problem effectively, (28) can be reformulated as

$$\max_{U_i\in\mathcal{S}, U_i\geq d_i, \forall i} \sum_{i=1}^{N} ln\,(U_i(\boldsymbol{\tau}) - d_i(\boldsymbol{\tau})) \tag{29}$$

Constraints: (9), (10), (11) and (12).

For the reformulated cooperative problem, we need to prove there exists a unique NBS that maximizes the objective function in (29). Note that the solution of (29) is applicable to (28) and $d_i(\boldsymbol{\tau})$ is set to be 0 [44].

1) EXISTENCE OF NASH BARGAINING SOLUTION

According to [43], there is at least one NBS to the problem (29) when $\mathcal{S}$ is a nonempty, convex, and compact set which is straightforward to see. Furthermore, we define $f = ln\,(U_i(\boldsymbol{\tau}) - d_i(\boldsymbol{\tau}))$. Then the second partial derivative can be obtained as

$$\frac{\partial^2 f}{\partial\tau_i^2} = -\frac{1}{U_i^2}\left(\frac{\partial U_i}{\partial\tau_i}\right)^2 + \frac{\partial^2 U_i}{\partial\tau_i^2}\frac{1}{U_i} - \sum_{j=i+1}^{N}\left(T\frac{u(P_{AP}|h_i|^2)}{U_i}\right)^2 \tag{30}$$

since $U_i = E_i^s$, $\frac{\partial^2 U_i}{\partial\tau_i^2} < 0$ according to (19). Therefore, we have the conclusion that $\frac{\partial^2 f}{\partial\tau_i^2} < 0$. As a result, the existence of the NBS is established.

2) UNIQUENESS OF NASH BARGAINING SOLUTION

According to [45], there exists a unique NBS to a cooperative game if and only if the following four conditions are satisfied.

- The strategy set $\mathcal{A}_i$ is nonempty.
- There exists $\tau_i \in \mathcal{A}_i$ satisfying $U_i \geq 0$.
- The utility function f is continuous and quasi-concave with respect to τ_i.
- The game model $\mathbb{G}_{BC}$ is diagonally strictly concave on its strategy set $\mathcal{A}_i$.

According to the above conditions, the following proposition is concluded.

Proposition 3: There exists a unique NBS in the formulated cooperative game $\mathbb{G}_{BC}$.

Proof: The first three conditions are directly satisfied by the proof of 1). The last condition is defined as

Definition 2: For any $\boldsymbol{\tau} \neq \boldsymbol{\tau'}$ and $\boldsymbol{\alpha} = [\alpha_1, \cdots, \alpha_N] \geq \mathbf{0}$, the following inequality holds [45]:

$$\left(\boldsymbol{\tau} - \boldsymbol{\tau'}\right)^T \boldsymbol{g}\left(\boldsymbol{\tau}, \boldsymbol{\alpha}\right) + \left(\boldsymbol{\tau'} - \boldsymbol{\tau}\right)^T \boldsymbol{g}\left(\boldsymbol{\tau'}, \boldsymbol{\alpha}\right) < 0$$

where the function is defined as

$$\boldsymbol{g}(\boldsymbol{\tau}, \boldsymbol{\alpha}) = \left[\alpha_1\frac{\partial f_1}{\partial\tau_1}, \cdots, \alpha_N\frac{\partial f_N}{\partial\tau_N}\right]^T$$

Based on *Definition 2*, we can derive that

$$
\begin{aligned}
&(\boldsymbol{\tau}-\boldsymbol{\tau}')^T\left[\boldsymbol{g}(\boldsymbol{\tau},\boldsymbol{\alpha})-\boldsymbol{g}(\boldsymbol{\tau}',\boldsymbol{\alpha})\right]\\
&=(\boldsymbol{\tau}-\boldsymbol{\tau}')^T\times\left[\alpha_1\left(\frac{\partial f_1}{\partial\tau_1}-\frac{\partial f_1}{\partial\tau_1'}\right),\cdots,\alpha_N\left(\frac{\partial f_N}{\partial\tau_N}-\frac{\partial f_N}{\partial\tau_N'}\right)\right]^T\\
&=\sum_{i=1}^{N}\alpha_i\left(\tau_i-\tau_i'\right)\left(\frac{\partial f_i}{\partial\tau_i}-\frac{\partial f_i}{\partial\tau_i'}\right)=\sum_{i=1}^{N}\theta_i
\end{aligned}
\tag{31}
$$

where $\theta_i = \alpha_i\left(\tau_i-\tau_i'\right)\left(\frac{\partial f_i}{\partial\tau_i}-\frac{\partial f_i}{\partial\tau_i'}\right)$. Due to the concavity of the utility function f, it is clear to observe that $\frac{\partial f_i}{\partial\tau_i}$ is monotonically decreasing with respect to τ_i. Therefore, for $\tau_i > \tau_i'$, $\left(\frac{\partial f_i}{\partial\tau_i}-\frac{\partial f_i}{\partial\tau_i'}\right) < 0$ and for $\tau_i' > \tau_i$, $\left(\frac{\partial f_i}{\partial\tau_i'}-\frac{\partial f_i}{\partial\tau_i}\right) < 0$. Since $\alpha_i > 0$, it can be concluded that $\theta_i < 0$ for all the cases. Therefore, the last condition is satisfied as well.

Based on the above analysis, we can conclude that there exists a unique NBS in the formulated game $\mathbb{G}_{BC}$.

3) BARGAINING COOPERATIVE ALGORITHM

In order to solve this Nash bargaining based time allocation problem with constraints, the well-known interior-point method is adopted. Note that this NBS is the optimal solution to the formulated problem (8). First, we define a function

$$L=\frac{1}{\sum ln(U_i)}+m\left(\sum(\tau_i-1)^2+\left(\sum\tau_i-1\right)^2\right) \tag{32}$$

$$l_i=\frac{\partial L}{\partial\tau_i} \tag{33}$$

where m is the barrier parameter.

IV. NUMERICAL RESULTS

In previous sections, all theoretical analyses and proof have been finished. In this section, we present several numerical results to illustrate and validate the aforementioned derivations and propositions. All devices are uniformly distributed with a centralized H-AP. The transmission power of the H-AP is set to be 500 mW, i.e., $P_{AP} = 0.5$ Watt. The downlink and uplink channel gains are assumed to be symmetric and subject to independent Rayleigh fading. In addition, by considering the path loss, the channel model is set to be $\mathbb{E}|h_i|^2 = \mathbb{E}|g_i|^2 = d_i^{-\alpha}$, where d_i is the distance between the H-AP and $IoTD_i$ and the path loss factor $\alpha = 2.5$ [46]. The required data volume D_i is set to be 15 Kbits, the frame length T is set to be 10s, and the bandwidth $B = 180$ KHz [33]. According to [35], we set $M = 24$ mW, $a = 1500$, and $b = 0.0014$ for the nonlinear energy harvesting model in (3). In addition, the original available energy, which ensures the initial operation of $IoTD_i$, is set to be $E_i^O = 0.1$ Joule and the initial energy harvesting time ratio $\tau_0 = 0.15$.

First of all, we consider a simple scenario with five IoT devices communicating with the H-AP to validate our proposed distributed non-cooperative algorithm (DNCA), where the circuit power consumption of IoT device P_c is set to be 5mW. Fig. 3 shows the convergence of our proposed DNCA. According to [40], there may exist multiple NEs if the identical convergence point cannot be achieved with random initial starting points. It can be easily observed that our proposed DNCA is capable of achieving the identical convergence point with different initial points, which means there exists a unique NE in the formulated game model $\mathbb{G}_{DNC}$. Fig. 4 shows the individual surplus energy of each IoT device. It is straightforward to observe that the surplus energy experiences an increase before the extreme point and a decrease

Algorithm 2 Bargaining Cooperative Algorithm

set bandwidth B, traffic volume D_i, circuit power consumption P_c, frame length T, initial $\boldsymbol{\tau}$ and the number of IoT device N;
for $k = k + 1$ **do**
  set $\tau_i = \boldsymbol{\tau}(i, k)$ and $m = \boldsymbol{M}(k)$;
  for $n = n + 1$ **do**
    $g_i = l_i(\tau_i, m)$
    if $\sqrt{\sum g_i^2} \le \epsilon$ **then**
      $\boldsymbol{\tau}(i, k + 1) = \tau_i$
      $F_0(k + 1) = L(\tau_i, m)$
    else
      $D_1 = \sum(\tau_i - dg_i)^2$
      $D_2 = e\big((\sum(\tau_i - dg_i) - 1)^2 + \sum(\tau_i - dg_i - 1)^2\big)$
      $D = D_1 + D_2$
      $dd = solve\left(\frac{\partial D}{\partial d} = 0\right)$
      $\tau_i = \tau_i - ddg_i$
    end if
  end for
  $\mathcal{T} = \sqrt{\sum(\boldsymbol{\tau}(i, k + 1) - \boldsymbol{\tau}(i, k))^2}$
  $\mathcal{F} = \left(\frac{F_0(k+1)-F_0(k)}{F_0(k)}\right)^2$
  if $\mathcal{T} \le \epsilon \&\& \mathcal{F} \le \epsilon$ **then**
    Output $\boldsymbol{\tau}(i, k + 1), F_0(k + 1)$
  else
    $\boldsymbol{M}(k + 1) = 10\boldsymbol{M}(k)$
  end if
end for

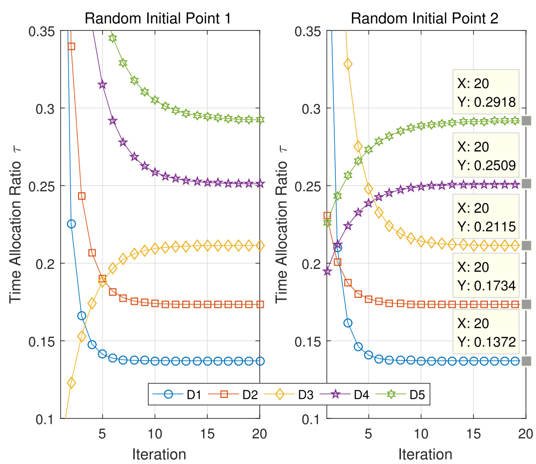

FIGURE 3. Convergence of distributed non-cooperative algorithm.

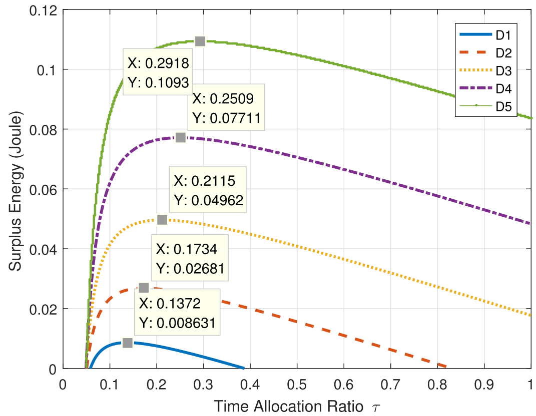

FIGURE 4. Surplus energy versus time allocation ratio τ with non-cooperative algorithm.

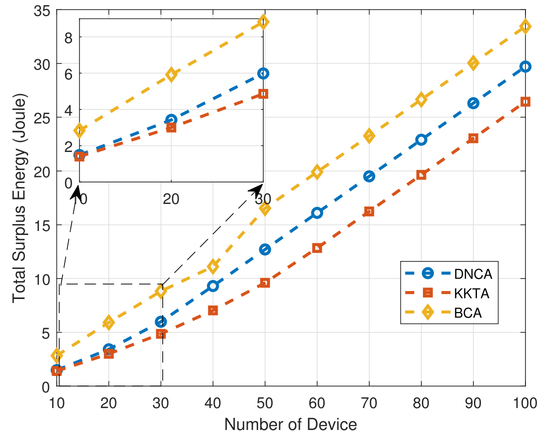

FIGURE 5. Total surplus energy versus the number of devices.

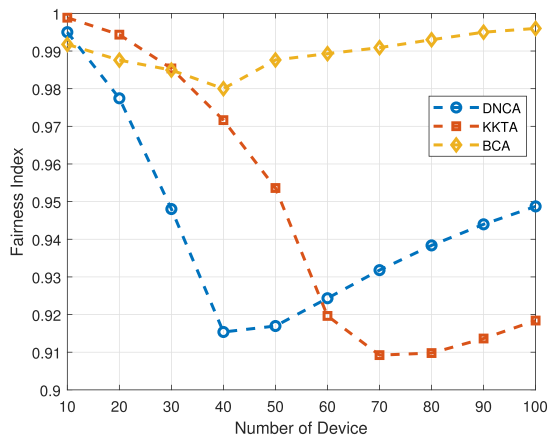

FIGURE 6. Fairness index versus the number of devices.

after this extreme point, which means there exists a maximum surplus energy for each IoT device. In addition, once we combine Fig. 3 and Fig. 4, it can be concluded that the maximum surplus energy in Fig. 4 is achieved by the convergence value in Fig. 3 (i.e., $D1(\mathbf{0.1372}, 0.008631)$in Fig. 4 is achieved via $D1(20, \mathbf{0.1372})$ in Fig. 3).

Next, we investigate the average total surplus energy and fairness of this wireless powered network in terms of device quantity and circuit power consumption. Note that the curves in the following figures are obtained over 10000 independent simulations. And in order to fully illustrate the superiority of our proposed game theory based algorithms, the well-known KKT condition based algorithm is involved as the benchmark in the system performance comparison. Note that since in most papers related to game theory and wireless power transmission, the non-cooperative game model is widely used due to its adaptability. Therefore, the performance of these non-cooperative game-based algorithms can be represented by our DNCA in this paper. Consequently, the comparisons actually involve the optimal cooperative game-based algorithm (BCA), the sub-optimal non-cooperative game-based algorithms represented by DNCA, and the benchmark algorithm named KKTA.

Fig. 5 illustrates the average total surplus energy of this wireless powered IoT network with fixed circuit power consumption (i.e., $P_c = 5$mW). It can be observed that our proposed DNCA and BCA always outperform KKTA regardless of the device quantity. And the BCA is always superior to the KKTA. The advantage is relatively small when the number of devices is small. This is because the limited time resource (i.e., $T = 10$s) is capable of accommodating the small number of devices (i.e., $N \leq 20$), which means the available energy E_i^A partly contributed by the harvested energy E_i^H is able to cover the consumed energy E_i^C. However, when the device quantity exceeds the system capacity (i.e., $N \geq 50$), part of the devices just store their available energy instead of uplink transmission, which results in the increase of total surplus energy as well as the total surplus energy gap.

Fig. 6 shows the impact of IoT device quantity on system fairness regarding the surplus energy. Note that the circuit power consumption is also fixed to be 5mW here. It is clear to observe that all these three curves experience a decrease first and then increase with the number of devices. The reason is that with the increase of devices, part of the devices has no time to do uplink transmission. Therefore, they turn to store all the available energy. Consequently, the distribution of the surplus energy becomes dispersed, which results in a decrease of fairness. However, when the number of devices exceeds a certain value (i.e., N=40 for DNCA, N=70 for KKTA and N=40 for BCA), the majority of the devices turns to purely store energy without uplink transmission. Hence, the distribution of the surplus energy concentrates again, which leads to an increase of the fairness. Note that there should exist a limitation for the number of devices served in one frame since the frame length is fixed. This upper bond depends on the overall channel condition, the required data volume of uplink transmission D_i and the frame length T. The fact is that with better channel condition, less data volume and longer frame length, more devices can be accommodated.

In Fig. 7, the impact of circuit power consumption on total surplus energy is investigated, where the number of devices

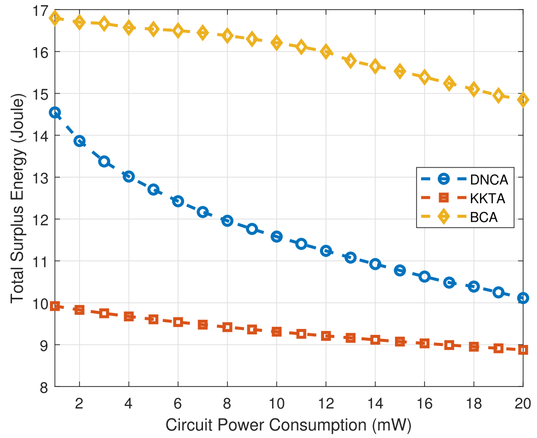

FIGURE 7. Total surplus energy versus circuit power consumption.

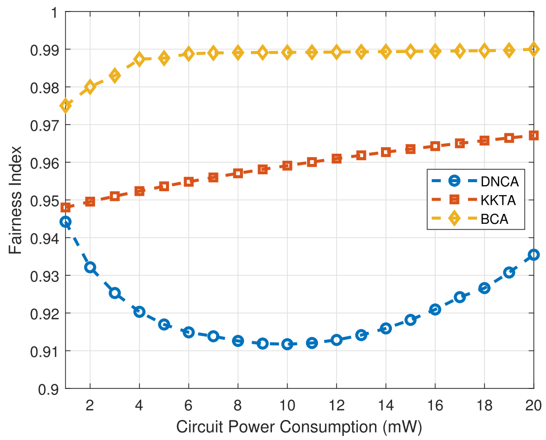

FIGURE 8. Fairness index versus circuit power consumption.

is set to be 50. Our proposed BCA and DNCA outperform the KKTA and all of them increase with the circuit power consumption since the increase of P_c necessarily decreases the surplus energy E_i^S based on (7). However, in Fig. 8 all curves experience a slight increase with the circuit power consumption generally. This is because once the circuit power consumption is high, the surplus energy of each individual device is compressed into a pretty small value, which makes the distribution of surplus energy more concentrated.

V. CONCLUSION

In this paper, two game theory based algorithms which address the time allocation problem in terms of surplus energy for wireless powered IoT networks are developed. The non-cooperative and cooperative game models are established, respectively. After proving the existence and uniqueness, the corresponding Nash equilibrium (NE) and Nash bargaining solution (NBS) are derived based on the formulated game model, which maximize the total surplus energy of the proposed network scenario. The numerical results validate our analysis about our proposed algorithms. Furthermore, the well-known KKT condition is adopted to make the comparison, where our proposed complicated BCA is always superior to the DNCA and KKTA in terms of the total surplus energy and system fairness. And the proposed DNCA outperforms KKTA regarding total surplus energy while it is inferior to KKTA in terms of fairness. Note that although the performance of BCA is overwhelming, the overhead for negotiations is huge due to the large number of devices which will be fully investigated in our future papers and it is possible to apply the proposed algorithms to some long-term cases and it is believed that with the assistance of a well-designed scheduling scheme, the long-term optimization will dramatically improve the system performance.

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