2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)

Dynamic Service Selection in Backscatter-Assisted RF-Powered Cognitive Networks: An Evolutionary Game Approach

Xiaozheng Gao*†, Shaohan Feng†, Dusit Niyato†, and Kai Yang*
*School of Information and Electronics, Beijing Institute of Technology, Beijing, China
†School of Computer Science and Engineering, Nanyang Technological University, Singapore

***Abstract*—Conventional radio-frequency-powered cognitive networks can be combined with the backscatter communication technology to improve performance of the networks. In this paper, we consider a backscatter-assisted radio-frequency-powered cognitive network, where many secondary transmitters transmit data to a common secondary gateway. The secondary gateway, as a controller, provides two services for the secondary transmitters, and the secondary transmitters will adapt their service selection when their utilities are below the expected utility. To analyze the service selection of the secondary transmitters, we formulate the problem as an evolutionary game. Specifically, we model the service adaptation of the secondary transmitters by the replicator dynamics, and analytically prove that a unique evolutionary equilibrium is reached by the evolutionary game. Also, we prove that the evolutionary equilibrium is stable. We further present numerical results to provide insights of the dynamic service selection in the network.**

***Index Terms*—energy harvesting, backscatter communications, service selection, evolutionary game.**

I. Introduction

Recently, the Internet of Things (IoT) architecture is expected to support a massive number of devices (e.g, sensors) connected to the network [1–3], and the energy harvesting technology, which can convert the RF signals into the electricity, has been deemed as a promising technique to supply the energy for the IoT devices to transmit data [4]. In RF-powered networks, a typical policy for the devices to transmit data is the harvest-then-transmit (HTT) mode [4]. Specifically, the devices, as the secondary transmitters (STs), harvest energy when there exist primary signals, and the STs use the harvested energy to transmit data when the primary channel is idle. However, when the primary channel is mostly busy, the performance (e.g., throughput) of the STs is very poor due to the limited transmission time.

To improve the performance of the STs, the backscatter communication, where the STs transmit data by backscattering ambient signals [5], is integrated with the HTT mode in the RF-powered networks [6–8]. In the backscatter-assisted RF-powered networks, the STs can choose the HTT mode and/or the backscatter mode to transmit data. Since an additional transmission mode is introduced in the backscatter-assisted RF-powered networks, the performance of the STs will be improved compared with that in the conventional RF-powered networks. Therefore, the backscatter-assisted RF-powered networks are receiving growing attention [6–8].

As a typical network setting of the backscatter-assisted RF-powered networks, multiple STs transmit data to a common secondary gateway (SG) [7]. Therefore, the time resource should be assigned to the STs carefully to avoid the interferences among the STs. The SG, as a controller, is responsible for assigning the time resource to the STs to transmit data, and pricing is an effective method to stimulate the SG to provide the time resource for the STs [7, 8]. To satisfy different quality of service requirements, the SG usually provides different services for the STs by assigning different amount of the time resource with different prices. It is notable that the STs choosing different services may achieve different utilities, and the STs with lower utilities have the incentives to adapt their service selection [9, 10]. Therefore, the service selection strategy for the STs changes over time. Evolutionary game, which can model the strategy adaptation of players, is a suitable tool to deal with the problem with dynamic strategies [11]. In addition, the strategy adaptation based on the evolutionary game has a low complexity [9, 11], which is attractive to the power-constrained systems. Hence, the above observations motivate us to apply the evolutionary game to investigate the dynamic service selection in backscatter-assisted RF-powered cognitive networks.

In this paper, we model the adaptation of the service selection of the STs by replicator dynamics in the evolutionary game, and analytically prove that a unique evolutionary equilibrium can be obtained in the game. We further prove that the obtained evolutionary equilibrium is stable. Simulation results are presented to show the insights of dynamic service selection in the network. To the best of our knowledge, this is the first work that applies the evolutionary game in the backscatter-assisted RF-powered cognitive networks.

The rest of this paper is organized as follows. In Section II, we briefly review the related work. The model of the dynamic service selection in a backscatter-assisted RF-powered network is presented in Section III. In Section IV, we formulate the service selection problem as an evolutionary game, and analyze the evolutionary equilibrium. Section V presents the numerical results, which are followed by the conclusions in Section VI.

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DOI 10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00146

II. Related Work

Although the study on the backscatter-assisted RF-powered cognitive network is at its infancy, there are still a few papers investigating how to improve the network performance by integrating the backscatter communication to the RF-powered cognitive network. In [6], the ambient backscatter communication was integrated with the RF-powered cognitive networks, and the authors derived a time resource assignment strategy to optimize the throughput of the ST. Considering the transmission demands of the STs, the authors in [7] utilized the auction approach to allocate the time resource for the STs in a backscatter-assisted RF-powered network. In [8], the Stackelberg game was employed to determine the price charged by the SG and the transmission periods in both the backscatter and the HTT modes for the STs. In [12], the authors derived both the optimal reflection coefficient and the optimal tradeoff between the energy harvesting time and the backscatter time, to maximize the network throughput. In [13], the optimal time resource assignment strategy, including (i) the time periods of the ambient backscatter mode and the energy harvesting and (ii) the time periods of the bistatic scatter mode and the HTT mode, was proposed to maximize the network throughput. However, all these studies do not investigate the dynamic adaptation of the STs' service selections in backscatter-assisted RF-powered networks.

Evolutionary game, which was originally adopted in biology, is a suitable tool to investigate the problem with dynamic strategies. Compared with traditional game theory, the evolutionary game has the following advantages [9, 11]. Firstly, when there are multiple Nash equilibrium solutions, a refined solution can be obtained in the evolutionary game. Secondly, the players in the evolutionary game adapt their strategies gradually and reach the solution eventually, which is different from the fact that the players in traditional games choose the desired solution immediately. Finally, the evolutionary game can track the dynamics and the trends of the players' strategies during the strategy adaptation. With the aforementioned advantages, the authors in [9] investigated the dynamics of network selection in heterogeneous networks, where both the population evolution and reinforcement-learning algorithms were developed. In [10], the authors formulated the resource allocation in small cells as an evolutionary game, and analysed the evolutionary equilibrium based on the stochastic geometry approach. In [14], the authors developed the incentive mechanism of spectrum sharing between the macro cell and the small cells by using the evolutionary game and the differential game. In [15], the evolutionary game was employed to model the dynamic processes of the information diffusion in three different networks. In [16], the authors adopted the evolutionary game to model the adaptation of the feedback rate of the channel state information, which was employed for the interference alignment in multiple-input-multiple-output networks. However, existing studies do not investigate the service selection in the backscatter-assisted RF-powered cognitive networks. Note that the utilities of the STs in the backscatter-assisted RF-powered networks are more complex due to the fact that the performances achieved by the two transmission modes are influenced by each other.

III. System Model

We now present the system model of the dynamic service selection in a backscatter-assisted RF-powered cognitive network, and then define the utilities of the STs choosing different services.

A. Network Model

We consider a backscatter-assisted RF-powered cognitive network, as shown in Fig. 1. In the network, the primary transmitter transmits signals on a periodic basis, where the normalized busy period and the normalized idle period are denoted as α and $1-\alpha$, respectively. There are a group of STs that want to transmit data to a common SG, and the number of the STs is N.

For the data transmissions from the STs to the SG, one typical method is the HTT mode. In the HTT mode, the STs harvest energy during the busy period, and use the harvested energy to transmit data during the idle period. In addition, the backscatter mode, where the STs backscatter the primary signals to the SG directly, is an essential supplement to the HTT mode. Accordingly, as the controller of the secondary network, the SG provides two services for the STs to transmit data. Specifically, in Service 1, the STs can transmit data only in the HTT mode, and in Service 2, the STs can transmit data in both the HTT mode and the backscatter mode. Let N_i denote the number of the STs choosing Service i ($i \in \{1, 2\}$). Accordingly, the proportion of the STs choosing Service i can be expressed as $x_i = N_i/N$.

To avoid the interference among the transmissions from the STs to the SG, the time division multiple access (TDMA) is adopted in the secondary network. In addition, the SG partitions the available idle time resource into two parts for Service 1 and Service 2, respectively. Let β denote the fraction of the idle period for Service 1. Accordingly, the normalized idle periods for Service 1 and Service 2 are $\beta(1-\alpha)$ and $(1-\beta)(1-\alpha)$, respectively. For a given service, the time period is equally assigned by the SG to the STs choosing the same service [9]. Accordingly, the idle period assigned by the SG for each ST choosing Service 1 is given by

$$\tau_1^{\text{idle}} = \frac{\beta(1-\alpha)}{x_1 N}. \tag{1}$$

Similarly, the busy and idle periods assigned by the SG for each ST choosing Service 2 are

$$\tau_2^{\text{busy}} = \frac{\alpha}{x_2 N} \tag{2}$$

and

$$\tau_2^{\text{idle}} = \frac{(1-\beta)(1-\alpha)}{x_2 N}, \tag{3}$$

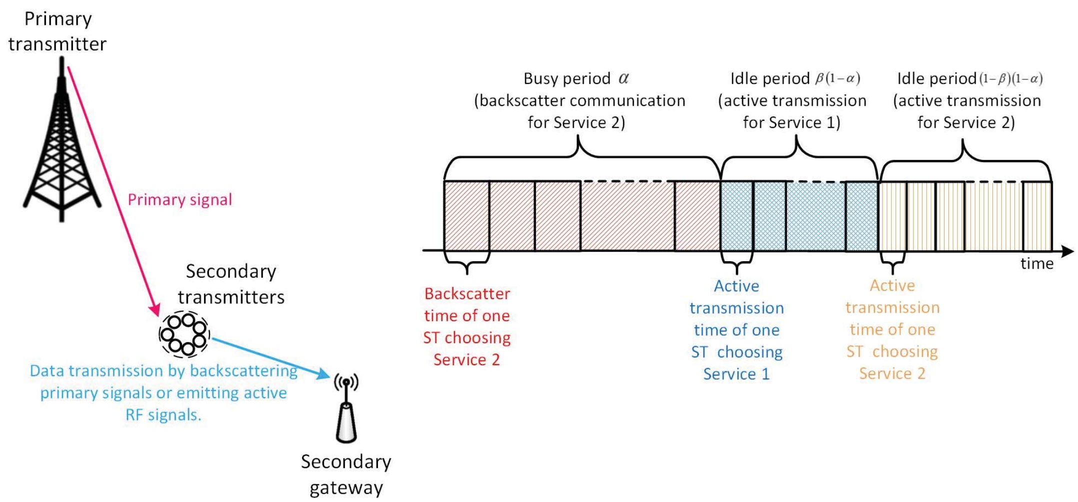

Fig. 1. System model.

respectively.

B. Utility Functions

We now present the utility functions of the STs when choosing different services. Similar to [14], we assume that the STs are statistically identical in location and propagation environment. Therefore, the STs choosing the same service have the same utilities. Specifically, for the STs choosing Service 1, only HTT mode can be employed by the STs. Therefore, the normalized energy harvesting period of each ST choosing Service 1 is α. Accordingly, the harvested energy of each ST choosing Service 1 is

$$E_1^{\mathrm{h}} = P_{\mathrm{h}}\alpha, \tag{4}$$

where P_{h} denotes the harvested power of one ST. As such, the amount of the transmitted data of each ST choosing Service 1 during one time unit is given by

$$Z_1 = \tau_1^{\mathrm{idle}} \xi B \log_2\left(1 + \frac{g_{\mathrm{st,sg}} E_1^{\mathrm{h}}}{\sigma^2 \tau_1^{\mathrm{idle}}}\right), \tag{5}$$

where B denotes the transmission bandwidth, ξ denotes the efficiency of the active transmission, $g_{\mathrm{st,sg}}$ denotes the channel gain between the STs and SG, and σ^2 is the power of the noise. Substituting (4) into (5), Z_1 can be rewritten as

$$Z_1 = \tau_1^{\mathrm{idle}} \xi B \log_2\left(1 + \frac{\varsigma\alpha}{\tau_1^{\mathrm{idle}}}\right), \tag{6}$$

where $\varsigma = g_{\mathrm{st,sg}} P_{\mathrm{h}}/\sigma^2$.

When the STs choose Service 2, both the HTT mode and the backscatter mode can be employed by the STs. Let τ_2^{b} denote the actual backscattering time period of each ST choosing Service 2. Accordingly, the amount of the transmitted data of each ST choosing Service 2 in the backscatter mode during one time unit can be given by

$$Z_2^{\mathrm{b}} = R^{\mathrm{b}} \tau_2^{\mathrm{b}}, \tag{7}$$

where R^{b} is the transmission rate of one ST transmitting data to the SG in the backscatter mode.

During the time period of one ST backscattering primary signals, the ST cannot harvest the energy which is used for the data transmission in the HTT mode [6]. Therefore, the normalized energy harvesting period of each ST choosing Service 2 is $\alpha - \tau_2^{\mathrm{b}}$. Accordingly, the harvested energy of each ST choosing Service 2 is

$$E_2^{\mathrm{h}} = P_{\mathrm{h}}(\alpha - \tau_2^{\mathrm{b}}). \tag{8}$$

Therefore, during one time unit, the amount of the transmitted data of each ST choosing Service 2 by using the HTT mode is given by

$$Z_2^{\mathrm{t}} = \tau_2^{\mathrm{idle}} \xi B \log_2\left(1 + \frac{g_{\mathrm{st,sg}} E_2^{\mathrm{h}}}{\sigma^2 \tau_2^{\mathrm{idle}}}\right). \tag{9}$$

Substituting (8) into (9), Z_2^{t} can be rewritten as

$$Z_2^{\mathrm{t}} = \tau_2^{\mathrm{idle}} \xi B \log_2\left(1 + \frac{\varsigma(\alpha - \tau_2^{\mathrm{b}})}{\tau_2^{\mathrm{idle}}}\right). \tag{10}$$

From (7)–(10), we find that an increase of the backscatter time will reduce the time period of harvesting energy, which results in the reduction of the amount of the transmitted data in the HTT mode. Therefore, the STs choosing Service 2 may not utilize all the available busy period for backscatter communications. Accordingly, the maximum amount of the transmitted data of each ST choosing Service 2 during one time unit can be expressed as

$$Z_2 = \max_{\tau_2^{\text{b}}} \ Z_2^{\text{b}} + Z_2^{\text{t}}, \\ s.t. \ \ 0 \le \tau_2^{\text{b}} \le \tau_2^{\text{busy}}. \tag{11}$$

Note that the optimization problem in (11) is a convex optimization problem with only one variable, and we can resort to existing optimization methods to solve it easily.

Let p_i denote the price charged by the SG for providing Service i for each ST. Accordingly, the utility (i.e., the payoff) of each ST choosing Service i, defined as the ratio of the amount of the transmitted data during one time unit and the price [14], can be expressed as

$$u_i = \frac{Z_i}{p_i}. \tag{12}$$

IV. Evolutionary Game Formulation and Analysis

In this section, we model the dynamic service selection of the STs in the backscatter-assisted RF-powered network by evolutionary game. In particular, we first present the formulation of the evolutionary game. We then prove important properties of the formulated evolutionary game, i.e., the existence and uniqueness, and the stability of the evolutionary equilibrium.

A. Evolutionary Game Formulation

We employ the evolutionary game to model the dynamic service selection of the STs in the network. Specifically, the players are the STs, and the strategy of each ST is the selection of different services (i.e., Service 1 and Service 2). The STs form a population. The payoff of each ST is defined in (12). Since x_i varies over time, we denote $x_i(t)$ as the value of x_i at time t. Accordingly, we denote $u_i(t)$ as the value of u_i at time t. Therefore, the expected utility of one ST at time t is given by

$$\bar{u}(t) = x_1(t)u_1(t) + x_2(t)u_2(t). \tag{13}$$

Then, we employ the replicator dynamics to model the service adaptation of the STs. Specifically, the replicator dynamic process of the STs is formulated as a series of ordinary differential equations (ODEs), as follows:

$$\dot{x}_i(t) = f_i(\boldsymbol{x}(t)) = \delta x_i(t)(u_i(t) - \bar{u}(t)), \forall i \in \{1, 2\}, \forall t, \tag{14}$$

with the initial state $\boldsymbol{x}(0) \in \mathcal{X}$, where $\boldsymbol{x}(t) = [x_1(t), x_2(t)]$, $\dot{x}_i(t)$ denotes the time derivative of $x_i(t)$ with respect to t, $\mathcal{X}$ is the set of all feasible states, and δ is a positive learning rate, which controls the speed of the strategy adaptation. From (13) and (14), if $x_1(0) + x_2(0) = 1$, we have

$$\dot{x}_1(t) + \dot{x}_2(t) = 0, \forall t, \tag{15}$$

and

$$x_1(t) + x_2(t) = 1, \forall t. \tag{16}$$

B. Existence and Uniqueness of the Evolutionary Equilibrium

To prove the existence and uniqueness of the evolutionary equilibrium, we first present the following lemma.

Lemma 1: $f_i(\boldsymbol{x}(t)), \forall \boldsymbol{x}(t) \in \mathcal{X}, \forall i \in \{1, 2\}$, is bounded.

Proof: From (1), (5), and (12), we have

$$x_1(t)u_1(t) = \frac{\xi B\beta(1-\alpha)}{p_1 N} \log_2\left(1 + \frac{\varsigma\alpha x_1(t) N}{\beta(1-\alpha)}\right), \tag{17}$$

from which we can easily conclude that $x_1(t)u_1(t)$ is bounded.

From (2), (3), (11), and (12), we have

$$h_{\min}(t) \le x_2(t)u_2(t) \le h_{\max}(t), \tag{18}$$

where

$$h_{\min}(t) = \frac{\xi B(1-\beta)(1-\alpha)}{p_2 N} \log_2\left(1 + \frac{\varsigma\alpha x_2(t) N}{(1-\beta)(1-\alpha)}\right) \tag{19}$$

and

$$h_{\max}(t) = \frac{R^{\text{b}}\alpha}{p_2 N} + h_{\min}(t). \tag{20}$$

Here, $h_{\min}(t)$ is obtained when $\tau_2^{\text{b}} = 0$ in (11), and $h_{\max}(t)$ is obtained when we ignore the reduction of the harvested energy due to the backscatter communications. From (19) and (20), we have that both $h_{\min}(t)$ and $h_{\max}(t)$ are bounded. Therefore, from (18), $x_2(t)u_2(t)$ is bounded. Accordingly, from (13), $\bar{u}(t)$ is bounded, from which we have that $x_i(t)\bar{u}(t)$ is also bounded. Recalling the fact that $x_i(t)u_i(t), \forall i \in \{1, 2\}$, is bounded, from (14), it immediately follows that $f_i(\boldsymbol{x}(t)), \forall \boldsymbol{x}(t) \in \mathcal{X}, \forall i \in \{1, 2\}$, is bounded, which completes the proof of Lemma 1. ■

Lemma 1 paves the way for proving the existence and uniqueness of the evolutionary equilibrium, which is given in the following theorem.

Theorem 1: For any initial state $\boldsymbol{x}(0) \in \mathcal{X}$, the evolutionary game with the system of ODEs in (14) is solvable, and its solution is unique.

Proof: From Lemma 1, we have that $f_i(\boldsymbol{x}(t)), \forall \boldsymbol{x}(t) \in \mathcal{X}, \forall i \in \{1, 2\}$, is bounded. In addition, from (12) and (14), we find that $f_i(\boldsymbol{x}(t)), \forall \boldsymbol{x}(t) \in \mathcal{X}$, is continuous. Therefore, there exists a positive parameter M, such that

$$\left|f_i(\boldsymbol{x}'(t)) - f_i(\boldsymbol{x}''(t))\right| \le M \left|\boldsymbol{x}'(t) - \boldsymbol{x}''(t)\right|, \\ \forall \boldsymbol{x}'(t), \boldsymbol{x}''(t) \in \mathcal{X}, \forall i \in \{1, 2\}, \forall t, \tag{21}$$

which indicates that $f_i(\boldsymbol{x}(t))$ satisfies the global Lipschitz condition. From the Cauchy-Lipschitz theorem [17], it follows that for any initial state $\boldsymbol{x}(0) \in \mathcal{X}$, the evolutionary game with the system of ODEs in (14) is solvable, and its solution is unique.

We now complete the proof of Theorem 1. ∎

From Theorem 1, we can conclude that a unique evolutionary equilibrium can be eventually reached in our formulated evolutionary game.

C. Stability Analysis of the Evolutionary Equilibrium

We now prove that the evolutionary equilibrium is stable, which is given in the following theorem.

Theorem 2: For any initial state $\boldsymbol{x}(0) \in \mathcal{X}$, the evolutionary equilibrium with the system of ODEs in (14) is stable.

Proof: Define a Lyapunov function as

$$L(\boldsymbol{x}(t)) = (x_1(t) + x_2(t))^2 . \tag{22}$$

From (22), we have

$$L(\boldsymbol{x}(t)) \begin{cases} = 0 & \text{if } \boldsymbol{x}(t) = \mathbf{0}, \\ > 0 & \text{otherwise.} \end{cases} \tag{23}$$

In addition, performing the first-order derivative of $L(\boldsymbol{x}(t))$ with respect to t, we have

$$\frac{d(L(\boldsymbol{x}(t)))}{dt} = 2\left(x_1(t) + x_2(t)\right)\left(\dot{x}_1(t) + \dot{x}_2(t)\right). \tag{24}$$

From (15), we have

$$\frac{d(L(\boldsymbol{x}(t)))}{dt} = 0. \tag{25}$$

Therefore, $L(\boldsymbol{x}(t))$ satisfies the required conditions of the Lyapunov function, which is defined in the Lyapunov's second method for stability [18]. Hence, based on the Lyapunov's second method for stability, it immediately follows that for any initial state $\boldsymbol{x}(0) \in \mathcal{X}$, the evolutionary equilibrium with the system of ODEs in (14) is stable.

We now complete the proof of Theorem 2. ∎

From Theorem 2, we can conclude that the obtained evolutionary equilibrium of our formulated evolutionary game is stable.

V. Numerical Results

We now present the numerical results to demonstrate the effectiveness of the proposed dynamic service selection strategy in the backscatter-assisted RF-powered cognitive network. Unless otherwise specified, we consider a network with a primary transmitter, an SG, and 100 STs. The normalized busy period is 0.7, and the fraction of the idle period for Service 1 is 0.5. The bandwidth is 0.1 MHz, and the transmission rate in the backscatter mode is 10 kbps. The prices for Service 1 and Service 2 are 0.5 and 1, respectively, and the learning rate is 10^{-4}.

We first investigate the state of the STs versus the evolutionary time. Figure 2 plots the proportions of the STs choosing different services over the evolutionary time with initial states (i) $\boldsymbol{x}(0) = [0.5, 0.5]$ and (ii) $\boldsymbol{x}(0) = [0.9, 0.1]$, respectively. From this figure, we find that the proportions of the STs choosing different services first adjust and then remain unchanged over the evolutionary time. During the beginning period, the STs adjust their strategies based on the replicator dynamics. Once the evolutionary equilibrium is reached, the proportions of the STs choosing different services remain unchanged. From this figure, we also find that with different initial states, the evolutionary equilibriums are the same.

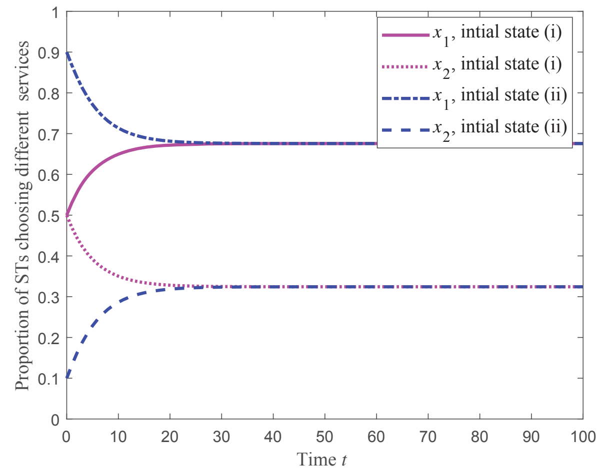

Fig. 2. Proportions of the STs choosing different services over time with initial states (i) $\boldsymbol{x}(0) = [0.5, 0.5]$ and (ii) $\boldsymbol{x}(0) = [0.9, 0.1]$.

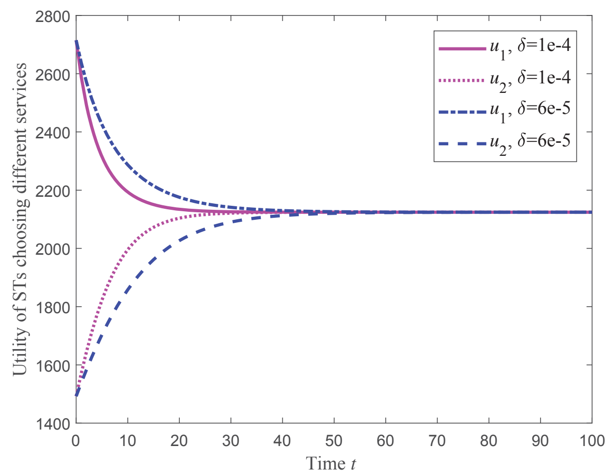

Fig. 3. Utilities of the STs choosing different services over time when $\boldsymbol{x}(0) = [0.5, 0.5]$ and $\delta = 1 \times 10^{-4}$ or 6×10^{-5}.

We next evaluate the utilities of the STs versus the evolutionary time. Figure 3 plots the utilities of the STs choosing different services versus the evolutionary time when $\boldsymbol{x}(0) = [0.5, 0.5]$ and $\delta = 1 \times 10^{-4}$ or 6×10^{-5}. From this figure, we observe that the utilities of the STs vary until the evolutionary equilibrium is achieved, which is consistent with Fig. 2. We also find that when the evolutionary equilibrium is reached,

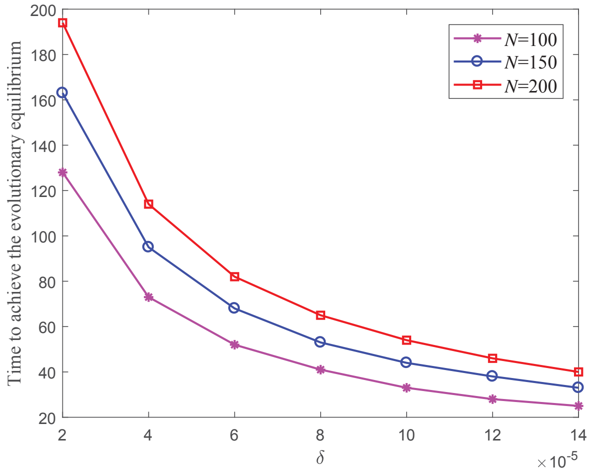

Fig. 4. Time to achieve the evolutionary equilibrium versus δ when $\boldsymbol{x}(0) = [0.5, 0.5]$ and $N = 100$, 150, or 200.

the STs can achieve the same utilities although they choose different services. This is due to the fact that the evolutionary equilibrium is achieved only when the utilities of the STs choosing any service are equal to the expected utility of the STs. In addition, we find that with different δ, the same evolutionary equilibrium is achieved.

We now discuss the impact of the learning rate δ on the service selection of the STs. Figure 4 plots the time to achieve the evolutionary equilibrium versus δ when $\boldsymbol{x}(0) = [0.5, 0.5]$ and $N = 100$, 150, or 200. We find that the value of δ influences the speed of achieving the evolutionary equilibrium. The larger the value of δ is, the faster the evolutionary equilibrium is achieved, which is consistent with the result in Fig. 3. In addition, we observe that the number of the STs N also influences the time to achieve the evolutionary equilibrium. With a given value of δ, the larger the value of N is, the more time is needed to achieve the evolutionary equilibrium.

VI. Conclusions

In this paper, we have investigated the dynamic service selection in a backscatter-assisted RF-powered cognitive network. In particular, we have formulated the service selection problem as an evolutionary game. In the evolutionary game, the STs dynamically adapt their strategies based on their own utilities and the expected utility, and an evolutionary equilibrium can be achieved by using the evolutionary game. We have proved that there exists a unique evolutionary equilibrium in our formulated game, and the evolutionary equilibrium is stable. The numerical results have been presented to provide insights of the dynamic service selection in the backscatter-assisted RF-powered cognitive network.

Acknowledgments

This work was supported in part by A*STAR-NTU-SUTD Joint Research Grant Call on Artificial Intelligence for the Future of Manufacturing RGANS1906, WASP/NTU M4082187 (4080), Singapore MOE Tier 1 under Grant 2017-T1-002-007 RG122/17, MOE Tier 2 under Grant MOE2014-T2-2-015 ARC4/15, Singapore NRF2015-NRF-ISF001-2277, Singapore EMA Energy Resilience under Grant NRF2017EWT-EP003-041, and National Natural Science Foundation of China under Grant 61771054.

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