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Research Article

Price-Based Resource Allocation in an UAV-Based Cognitive Wireless Powered Networks

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In recent years, unmanned aerial vehicle (UAV) has gained a lot of attention, mostly due to its low cost, flexile deployment, and broad applications in many fields such as military, agriculture, and environment. In this paper, an UAV-based cognitive radio (CR) network with a wireless powered primary user (PU) is investigated, where the UAVs act as the secondary users (SUs). We assume that one transmission time slot is divided into two phases. In the first phase, UAVs transmit information to base station (BS), while the PU harvests energy from the radio frequency (RF) signals, and the second phase is exclusively occupied by PUs for primary transmission. It is assumed that the PU prices the interference energy incurred from the UAVs for the reason that UAVs need to access PU's licensed spectrum for their transmission. In this paper, we aim at maximizing utilities of UAVs and utility of PU simultaneously. To analyze the interaction between the UAVs and PU, Stackelberg game was adopted where the UAVs act as followers and the PU acts as a leader. An alternating iterative algorithm is proposed to achieve the Stackelberg equilibrium (SE), i.e., transmission power of PU and UAVs, time allocation, and price that PU charge UAVs. According to the simulation results, the proposed scheme can achieve optimal utility in the view of power saving for UAVs while meeting the requirements of the PU which demonstrate the effectiveness of the proposed scheme.

1. Introduction

With the rapid development of mobile communication technology, communication systems (5G and beyond 5G) with high data rate, wide coverage, large bandwidth, and optimized user experiences are more attractive for people [1, 2]. Moreover, artificial intelligence (AI) creates opportunities to accelerate the development of 5G networks [3–5]. AI, 5G technologies, and the Internet of Things (IoT) [6–11] are advancing at a rapid pace, enabling a wide range of new applications. As an important application scenario of 5G mobile communication technology, unmanned aerial vehicles (UAVs), also known as "drones," have attracted more and more attention from international academic cycles and industry [12–15]. Compared with the traditional ground communication, UAV-based wireless communication systems have the advantages of flexible deploy, low cost, and additional design degrees of freedom, which can be applied to aerial surveillance, goods delivery, precision agriculture, civil infrastructure inspection, and so on [16].

Although UAV has enormous potential for application, it still faces many problems and challenges [17–21]. Considering the complexity of the development stages and the component integration complexity, challenges of developing UAV applications from the information technology project management point of view were investigated in [17]. The authors of [18] analyzed the difficulties and challenges for cooperation of multiple networked UAVs. The tradeoffs and challenges in UAV-enabled wireless networks are investigated. More specifically, the key UAV challenges such as 3D deployment, channel modeling, performance analysis, and energy efficiency (EE) were explored in [19]. The challenges of UAVs in smart cities, such as safety, privacy, and ethical uses, were investigated in [20]. Moreover, spectrum policy challenges of UAVs were analyzed in [21].

Among these challenges abovementioned, one of the important challenges is the spectrum scarcity issue in UAV networks [22]. Existing UAV-based communications rely mostly on the unlicensed spectrum or sharing the licensed spectrum, which suffer severe interference from a variety of other wireless networks (e.g., Wi-Fi, Bluetooth, and WiMAX) or the cellular networks. On the other hand, UAV communications also inevitably result in interference to other communication systems, which seriously degrades the system performance. Hence, how to solve these problems has become an important issue in the development of UAV communications.

Cognitive radio (CR) technology [23], which is regarded as a promising solution to combat the spectrum scarcity, has been considered to integrate with the UAV communications [24]. CR network is considered as an intelligent network, in which the secondary users (SUs) are able to sense the spectrum of primary users (PUs) and opportunistically access the spectrum resource, which significantly improves the spectrum utilization and communication quality. Overlay and underlay are two typical spectrum sharing modes in CR [25]. In the former mode, SUs sense the spectrum resource and access the idle spectrum, and in the latter mode, SUs and PUs are allowed to transmit simultaneously as long as the interference level at the PUs' side remains acceptable. Therefore, UAV communications can greatly benefit from the integration with CR in spectrum utilization, delay reduction, and energy consumption reduction.

UAV communication integrated with CR has various potential application scenarios such as commercial drones, traffic surveillance, crop monitoring, border patrolling, disaster management, and wildfire monitoring [26]. There are some works that considered the UAV communications is integrated with CR technology [27–31]. A new spectrum sharing scenario between UAV and terrestrial wireless communication systems was investigated in [27], and the average achievable rate of the cognitive UAV communications is maximized by jointly optimizing the UAV's trajectory and transmit power. The authors of [28] proposed an efficient energy management solution to improve the performance of the UAV and considered the effects of spectrum sensing simultaneously. An UAV-based CR was proposed to improve spectrum sensing performance, with the objective of maximizing the effective throughput of the UAV by optimizing the sensing radian in [29]. The authors of [30] investigated the multiaccess CR system using MIMO antennas for PUs and SUs supported by a UAV relay. A novel spectrum sharing-based UAV network with adjustable UAV beamwidth was proposed in [31].

Furthermore, energy management is also very important in UAV communications in association with CR networks. The optimal wireless information transfer and wireless energy transfer design for an UAV-enabled CR system was studied in [32], where both the UAV and the ground terminal were battery-powered. The authors of [33] proposed an efficient spectrum and energy management solution by integrating the overlay cognitive radio technology. The deployment of UAV-based cognitive system in an area covered by the primary network (PN) was studied in [34] with the aim at maximizing its EE by optimizing the transmit power. The authors of [35] studied interference reduction and resource allocation in UAV wireless powered communication system with two UAVs and two ground nodes. A problem of maximizing the percentage of scheduled UAVs by jointly optimizing UAV scheduling and wireless resource allocation was analyzed in [36].

In addition, the authors of [37] aim at maximizing the energy efficiency of the cognitive UAV-assisted traffic offloading in heterogeneous environments. The secrecy outage probability (SOP) for a multitier UAV-assisted cognitive communication network was investigated in [38]. An UAV-assisted energy harvesting cognitive radio network was considered in [39], where an UAV is employed as one cognitive user, hovering in the air to perform spectrum sensing and communicating with the dedicated receiver on the ground. The throughput performance of a NOMA-based UAV-assisted cooperative CR network was analyzed in [40], where the UAV harvests energy from terrestrial radio frequency (RF) signal sources. To our best knowledge, the energy management problem of UAV-based CR network is a new challenge, and there are very few research works concentrating on this aspect for UAV-enabled cognitive networks.

Different from the existing works, in this paper, we investigate the resource allocation problem in an UAV-based cognitive network, in which the PU is wirelessly powered by the energy harvested from the RF signals transmitted by the SUs. It is assumed that the PU is a low-power terminal. The UAVs, who act as SUs, are used to perform the ground surveillance and report the ground situation to the base station (BS). Energy management will affect the system performance, so we try to maximize the utilities of both PU and UAVs under some practical constraints. The time slot is divided into two phases, in which the first phase is used for UAVs' transmission and PU's energy harvesting and the second phase is used for PU transmitting. Stackelberg game is adopted to analyze the interaction between PU and SUs where the PU acts as the leader who determines the time allocation, the transmission power of PU, and the interference energy prices for UAVs, and the UAVs act as the followers who determine the transmission power of UAVs. The main contributions of this paper are as follows:

(i) We investigate the resource allocation problem aiming at the maximization of utilities of UAVs and utility of PU simultaneously

(ii) By transforming a nonlinear fractional programming problem into an equivalent parametric programming, we maximize the utilities of UAVs from the perspective of power saving, and then both the objectives abovementioned are optimized

The organization of this paper is as follows. In Section 2, the system model of the UAV-based CR networks is described. The problem formulation based on Stackelberg game under several constraints is analyzed in Section 3. An alternating iterative optimization algorithm is proposed in Section 4. Numerical results and analysis are given in Section 5. Finally, the whole paper is concluded in Section 6.

2. System Model

As shown in Figure 1, we consider an uplink transmission scenario. The UAV-based CR network is composed of a BS, a PU, and N SUs, where the UAVs act as the SUs who report the ground information to BS. It is assumed that the PU is wirelessly powered by RF signals harvested from UAVs' transmission. We assume that all UAVs are travelling or hovering a uniform height of H m, and their onboard energy capacity can afford an operation cycle of one hour, which can be divided into several time slots. In each slot, the time is normalized to 1, and the whole communication process is divided into two phases. The first phase with duration τ_0 is used for UAVs' transmission and energy harvesting of PU. In the second phase, PU transmits information to BS with duration $\tau_1 (\tau_1 = 1 - \tau_0)$.

Let h_0, h_n, and w_n denote the channel power gains from PU to BS, from UAV n to BS, and from UAV n to PU, respectively, where $n \in \{1, 2, \cdots, N\}$. Assume that these channel power gains are all independent and identically distributed (i.i.d.) random variables. The additive white Gaussian noise (AWGN) is with zero mean, and variance σ^2 is considered at the receivers.

2.1. Channel Model. Without loss of generality, the Cartesian coordinate system is adopted to determine the 3D location of UAVs. Note that $x(n)$ and $y(n)$ denote the time-varying x- and y-coordinates, respectively. The locations of the UAV n can be denoted as$(x[n], y[n], H)$. And the locations of the BS and PU are assumed to be $(x_0, y_0, 0)$ and $(x_1, y_1, 0)$, respectively.

For convenience, it is assumed that the paths from UAVs to BS or PU are referred to as the line of sight (LoS) link where the free space path model is adopted [41], and the Doppler effect is perfectly compensated. Accordingly, the channel power gain between UAV n and BS is given by

$$h_n = \beta_0 d_{ub}^{-2}[n], \tag{1}$$

and the channel power gain between UAV n and PU is written as

$$w_n = \beta_0 d_{up}^{-2}[n]. \tag{2}$$

β_0 denotes the channel power gain at the reference distance $d_0 = 1$ m. $d_{ub}[n]$ and $d_{up}[n]$ denote the distances from UAV n to BS and PU, respectively, which can be obtained by

$$d_{ub}[n] = \sqrt{H^2 + (x[n] - x_0)^2 + (y[n] - y_0)^2}, \tag{3}$$

$$d_{up}[n] = \sqrt{H^2 + (x[n] - x_1)^2 + (y[n] - y_1)^2}. \tag{4}$$

2.2. Transmission Model. In this UAV-based CR networks, the transmission model between the UAV n and BS is given by

$$L_n = \sqrt{h_n} s_n + \varphi_n, \tag{5}$$

where s_n is the information transmitted from UAV n to BS and φ_n is the noise. Considering that the UAVs only transmit during the time τ_0, the corresponding transmission rate is as follows:

$$R_U^n = \tau_0 \log_2\left(1 + \frac{P_n h_n}{\sigma^2}\right), \tag{6}$$

where P_n denotes the transmit power of UAV n to BS and σ^2 denotes the noise power.

Similarly, the transmission model between the PU and BS is given by

$$L_P = \sqrt{h_0} s_0 + \varphi_0, \tag{7}$$

where s_0 is the information transmitted from PU to BS and φ_0 is the noise. Considering that the PU only transmits during the time τ_1, the corresponding transmission rate is as follows:

$$R_P = \tau_1 \log_2\left(1 + \frac{P_P h_0}{\sigma^2}\right), \tag{8}$$

where P_P denotes the transmit power of PU.

It is assumed that the PU can harvest energy from RF signals of UAVs, and the harvested energy during time τ_0 can be given by

$$E_P = \varepsilon \tau_0 \sum_{n=1}^{N} P_n w_n, \tag{9}$$

where E_P denotes the total harvested energy of PU and ε denotes the energy harvesting efficiency.

For PU, after the energy harvesting during τ_0, it will transmit information. Note that the energy consumed by PU during τ_1 should not exceed the harvested energy during τ_0. Therefore, the following constraint must hold:

$$P_P \tau_1 \le E_P. \tag{10}$$

3. Problem Formulation

Based on above analysis, Stackelberg game is adopted to study the interaction between UAVs and the PU, and the corresponding utilities are given below.

We assume that the PU sets the interference prices for UAVs and the utility of PU can be formulated as follows:

$$U_P = \xi \tau_1 \log_2\left(1 + \frac{P_P h_0}{\sigma^2}\right) + \tau_0 \sum_{n=1}^{N} P_n w_n \pi_n, \tag{11}$$

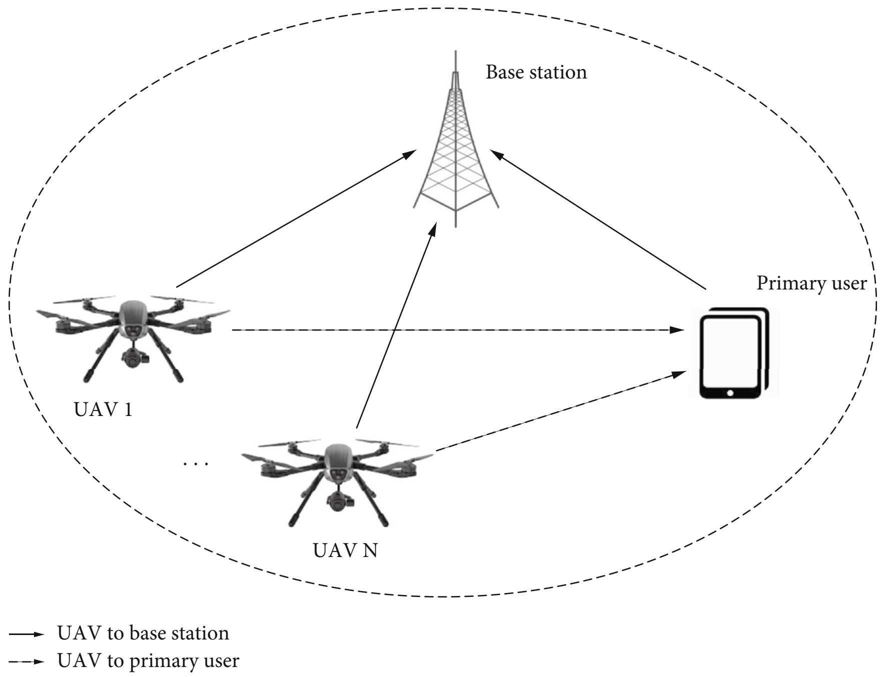

Figure 1: An illustrative example of the cognitive radio network with secondary UAVs.

where ξ is the unit rate utility factor for PU and π_n denote the interference power price of UAV n.

And the utility of UAV n can be formulated by

$$U_U^n = \frac{\alpha\tau_0 \log_2\left(1 + \left(P_n h_n/\sigma^2\right)\right) - \tau_0 \pi_n P_n w_n}{P_n + P_C}, \tag{12}$$

where α is the unit rate utility factor for UAVs and P_C denotes the additional circuit power consumption during transmission, which is independent of data transmission power. The optimization problem is formulated as

$$\begin{aligned} (\text{OP1}):\quad & \max_{\{P_n\}} U_U^n \\ \text{s.t.}\quad & P_n \geq 0. \end{aligned} \tag{13}$$

Note that the utility of UAV n takes into account the power consumption to prolong the service time of UAVs.

For PU, the objective is to maximize its utility by optimizing transmit power P_P, time allocation τ_0 and τ_1, and interference power price π_n in each slot. The problem is formulated as

$$\begin{gathered} (\text{OP2}): \max_{\{P_P,\pi_n,\tau_0,\tau_1\}} U_P \\ \text{s.t.} P_P \tau_1 \leq E_P \\ \tau_0 + \tau_1 = 1 \\ \pi_n \geq 0, P_P \geq 0, \tau_0 \geq 0, \tau_1 \geq 0. \end{gathered} \tag{14}$$

OP1 and OP2 together form a leader-follower game. The objective of this game is to find the SE point(s) from which neither the leader nor the followers have incentives to deviate. The SE point(s) can be obtained by solving the optimal transmission parameters abovementioned.

4. Resource Allocation Algorithm

In this game, the SE of OP1 and OP2 can be found by solving OP1 with given P_P, π_n, τ_0, and τ_1 and then solving OP2 with the obtained solution of OP1 [42].

4.1. Analysis of the Follower-Level Game. It is noteworthy that the OP1 is a nonlinear fractional programming problem, which is difficult to solve directly. To tackle this problem, an equivalent parametric programming model is deduced from OP1 by consulting the theory of [43], and the mathematical description can be briefly given as follows. We denote the optimal parameter q^* as

$$q^* = \max \frac{N(P_n)}{D(P_n)}, \tag{15}$$

where

$$N(P_n) = \alpha\tau_0 \log_2\left(1 + \frac{P_n h_n}{\sigma^2}\right) - \tau_0 \pi_n P_n w_n, \tag{16}$$

$$D(P_n) = P_n + P_C. \tag{17}$$

Let $F(q) = N(P_n) - qD(P_n)$, which is a linear function of q. Therefore, solving the OP1 is equal to find the zero root of $F(q) = 0$ [43]. Then, the OP1 can be transformed into OP3 as follows:

$$\begin{aligned}(\text{OP3}):\ &\max_{\{P_n\}} U_T^n = U_U^n - q(P_n + P_C)\\ &\text{s.t.}\quad P_n \geq 0.\end{aligned} \tag{18}$$

It can be easily observed that the objective function of OP3 is convex and the optimal solution P_n^* can be obtained by setting the first derivative of U_T^n to zero as

$$\frac{\alpha h_\text{n}}{\ln 2(\sigma^2 + P_n h_n)} - \pi_n w_n - q = 0, \quad \forall n, \tag{19}$$

from which we can derive the close-form solutions for P_n as follows:

$$P_n = \left(\frac{\alpha}{\ln 2}\frac{1}{\pi_n w_n + q} - \frac{\sigma^2}{h_n}\right)^+, \tag{20}$$

with $(\cdot)^+ \triangleq \max(\cdot,0)$.

Based on the obtained best responses of the UAVs obtained in Equation (20), we investigate the OP2 with an alternating iterative method.

4.2. Analysis of the Leader-Level Game. Firstly, we solve the OP2 with given P_P and π_n; then, the optimal time allocation with τ_0 and τ_1 can be obtained. Let $\tau_0 = 1\text{-}\tau_1$ and the OP2 can be rewritten as

$$\begin{aligned}(\text{OP2.1}):\ &\max_{\{\tau_1\}} \tau_1 \xi \log_2\left(1 + \frac{P_P h_0}{\sigma^2}\right) + (1 - \tau_1)\sum_{n=1}^{N} P_n w_n \pi_n\\ &\text{s.t.}\quad P_P \tau_1 \leq E_P.\end{aligned} \tag{21}$$

It can be obviously found that the objective function and the constraint are linear with respect to τ_1 and the optimal solution can be obtained by

$$\tau_1 = \left(\frac{\varepsilon \sum_{n=1}^{N} P_n w_n}{\varepsilon \sum_{n=1}^{N} P_n w_n + P_P}\right)^+. \tag{22}$$

Therefore, the optimal τ_0 can be derived easily as

$$\tau_0 = \left(\frac{P_P}{\varepsilon \sum_{n=1}^{N} P_n w_n + P_P}\right)^+. \tag{23}$$

Secondly, we solve OP2 with given τ_0, τ_1, and π_n; then, the optimal transmit power of PU with P_P can be obtained. We rewrite the OP2 as follows.

$$\begin{aligned}(\text{OP2.2}):\ &\max_{\{\text{P}_\text{P}\}} \xi(1\text{-}\tau_0)\log_2\left(1 + \frac{\text{P}_\text{P}\text{h}_0}{\sigma^2}\right)\\ &\text{s.t.} P_P \tau_1 \leq E_P.\end{aligned} \tag{24}$$

Since problem OP2.2 of optimizing P_P is convex, it can be solved by the dual decomposition method [44]. The Lagrangian dual function corresponding to Equation (24) can be formulated as

$$\begin{aligned}g(\lambda) &= \max_{\{P_P\}} L(\{P_P\}, \lambda) = \xi(1 - \tau_0)\log_2\left(1 + \frac{P_P h_0}{\sigma^2}\right)\\ &\quad + \lambda\left(\varepsilon\tau_0 \sum_{n=1}^{n} P_n w_n - P_P(1\text{-}\tau_0)\right),\end{aligned} \tag{25}$$

where λ is the introduced Lagrange dual multipliers (LDM); then, the dual optimization problem can be formulated as

$$\begin{aligned}&\min_{\{\lambda\}} g(\lambda)\\ &\text{s.t.}\lambda \geq 0.\end{aligned} \tag{26}$$

Applying Karush-Kuhn-Tucker (KKT) condition [45] by taking the first derivation of $L(\{P_P\}, \lambda)$ with respect to P_P, we have

$$P_P = \left(\frac{\xi}{\lambda \ln 2} - \frac{\sigma^2}{h_0}\right)^+, \tag{27}$$

and subgradient method is adopted to update λ which can guarantee to converge to the global optimal solution. The LDM λ is updated as follows:

$$\lambda^{l+1} = \left(\lambda^l - \theta_\lambda^l\left(\varepsilon\tau_0 \sum_{n=1}^{n} P_n w_n - P_P(1 - \tau_0)\right)\right)^+, \tag{28}$$

where l denotes the iteration index and θ_λ^l is the proper positive step-size sequence. After the convergence of the LDM, the optimal solution P_P^* can be obtained by substituting λ^* into Equation (27).

Thirdly, we solve OP2 with given τ_0, τ_1, and P_P; then, the optimal interference price with π_n can be obtained. Accordingly, we rewrite the OP2 as follows.

$$(\text{OP2.3}):\ \max_{\{\pi_n\}} \tau_0 \sum_{n=1}^{n} P_n w_n \pi_n. \tag{29}$$

Let U_π denote the objective function of OP2.3; then, the optimal interference price π_n can be obtained through solving the following equation:

$$\frac{\partial U_\pi}{\partial \pi_n} = \tau_0 w_n\left(\frac{\partial P_n}{\partial \pi_n}\pi_n + P_n\right) = 0, \tag{30}$$

which can be simplified and transformed into

$$\pi_n = -\frac{P_n}{\partial P_n / \partial \pi_n}. \tag{31}$$

In order to obtain the π_n, the PU needs to know the exact and prompt feedback information regarding the P_n and $\partial P_n/\partial \pi_n$; then, the interference price π can be updated according to the formula below:

$$\pi = S(\pi), \tag{32}$$

where $\pi = [\pi_1,\cdots,\pi_N]$ and

$$S(\pi) = [S(\pi_1),\cdots,S(\pi_N)] \tag{33}$$

denotes interference price competition constraint for PU. Therefore, the update process of price π_n can be modeled by an iterative formula as follows:

$$\pi(t+1) = S(\pi(t)). \tag{34}$$

Based on the Stackelberg game analysis and the updating formulas of these parameters, the PU can obtain the optimal interference price and transmit power and time allocation. Then, the UAVs would transmit with the optimal transmit power.

Note that the abovementioned problem-solving is based on the assumption that the parameter q is a constant. However, our ultimate aim is to find the solution of $F(q) = 0$. Because the $F(q)$ is strictly monotonic decreasing with respect to q, the optimal solution can be obtained if and only if when $F(q) = 0$. A bisection method can be adopted to search the optimal solution q^*. In summary, the proposed resource allocation algorithm is shown in Algorithm 1.

4.3. Existence and Uniqueness of SE for the Proposed Game. For the proposed game, the SE is defined as:

Definition 1. Let P_n^* be the solutions for OP1 and P_P^*, π_n^*, τ_0^* and $\tau_1^*(1-\tau_0^*)$ be the solutions for OP2. Then, the point ($P_n^*, P_P^*, \pi_n^*, \tau_0^*$) is a SE point if for any $(P_n, P_P, \pi_n, \tau_0)$ with $P_n \geq 0$, $P_P \geq 0$, $\pi_n \geq 0$, and $0 \leq \tau_0 \leq 1$, the following conditions are satisfied:

$$U_U^n(P_n^*, \pi_n^*, \tau_0^*) \geq U_U^n(P_n, \pi_n^*, \tau_0^*)\forall n, \tag{35}$$

$$U_P(\pi_n^*, P_P^*, \tau_0^*, P_n^*) \geq U_P(\pi_n, P_P^*, \tau_0^*, P_n^*)\forall n, \tag{36}$$

$$U_P(\pi_n^*, P_P^*, \tau_0^*, P_n^*) \geq U_P(\pi_n^*, P_P, \tau_0^*, P_n^*)\forall n, \tag{37}$$

$$U_P(\pi_n^*, P_P^*, \tau_0^*, P_n^*) \geq U_P(\pi_n^*, P_P^*, \tau_0, P_n^*)\forall n. \tag{38}$$

Theorem 2. *The Stackelberg equilibrium (SE) could always exist in the proposed Stackelberg game.*

Proof of Theorem 2. According to the game theory for wireless engineers, it could be found that if a game model satisfies both of the following criteria, there exists a Nash equilibrium (NE).

(i) Strategy space is a nonempty and bounded compact convex subset of Euclidean space

(ii) The utility function is a kind of quasiconcave (quasiconvex) function with respect to the parameters of strategy space

□

Given the PU's transmission power P_P, interference power price π_n, and energy harvesting time τ_0, it is obvious that the strategy space $\{P_n\}$ meets the first condition for the existence of NE because $\{P_n\}$ is a nonempty, bounded, and closed set, as well as a compact convex set. Besides, the utility function $U_T^n(P_n)$ is continuous and concave with respect to P_n.

Based on [46], there exists at least one NE in the follower subgame. $\mathrm{NE}(P_n)$ denotes the best response of the UAV (follower) with given transmission strategy of PU. The SE can be equivalently defined as

$$U_P(\pi_n^*, P_P^*, \tau_0^*, \mathrm{NE}(P_n^*)) \geq U_P(\pi_n, P_P, \tau_0, \mathrm{NE}(P_n)). \tag{39}$$

Therefore, the SE always exists in the proposed game.

Theorem 3. *There exists a unique SE for the proposed Stackelberg game.*

Proof of Theorem 3. The first-order partial derivative of U_T^n with respect to P_n can be found in Equation (19), and the corresponding second-order partial derivative of U_T^n is as follows:

$$\frac{\partial^2 U_T^n}{\partial P_n^2} = -\frac{\alpha h_n^2}{\ln 2(\sigma^2 + P_n h_n)^2} < 0. \tag{40}$$

□

Thus, the UAV's utility function $U_T^n(P_n)$ is a concave function of P_n given the PU's transmission strategy. Therefore, there exists a unique best response $NE(P_n^*)$ for the UAV n.

Based on the above analysis, there exists a unique SE in the proposed game.

5. Numerical Results

In this section, some numerical results are presented to verify the performance of the proposed resource allocation scheme in cognitive UAV networks. For the convenience of solving this problem, we consider a scenario with two UAVs and one PU. It is assumed that the channel power gains h_0, $\mathbf{h}$ and $\mathbf{w}$ are Rayleigh distributed random variances with means -6 dB. σ^2 is assumed to be 0.1.

To evaluate the performance of the proposed scheme, we present the simulation results of both the UAV's utility and the PU's utility with different system parameters. For the purpose of comparison, two reference schemes are provided. The former one is named as scheme 2 which assumes that the time is equally allocated as $\tau_0 = \tau_1 = 0.5$, while the latter

Initialization:

$\mathbf{h}, \mathbf{w}, h_0, \sigma, \xi, \varepsilon, \delta, P_C, a, \tau_0(0), \boldsymbol{\pi}(0), P_P(0), \mathbf{P}(0), a$ and b(error limitation $\delta > 0$, a, b satisfying $F(a) > 0$ and $F(b) > 0$; $q = (a + b)/2$;

Iteration:

1): **while**$|F(q)| > \delta$**do**
2): k = 1;
3): Calculate the updated parameters by using Equations (20), (23), (27), and (31);
4): **while**$|\mathbf{P}(k) - \mathbf{P}(k-1)| > \delta$ or $|\boldsymbol{\pi}(k) - \boldsymbol{\pi}(k-1)| > \delta$ or $|\tau_0(k) - \tau_0(k-1)| > \delta$ or $|P_P(k) - P_P(k-1)| > \delta$**do**
5): update $\mathbf{P}(k), P_P(k), \boldsymbol{\pi}(k), \tau_0(k)$ accordingly;
6): k = k + 1;
7): **end while**
8): **if**$F(a) \cdot F(b) \geq 0$ then
9): $a = q$;
10): **else**
11): $b = q$;
12): **end if**
13): $q = (a + b)/2$;
14): **end while**

Algorithm 1: Resource allocation scheme.

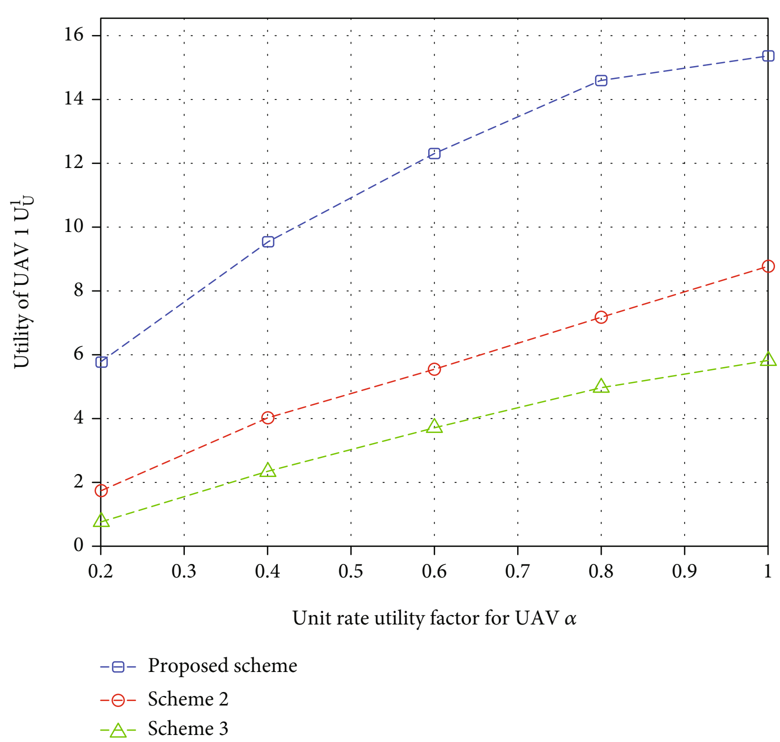

Figure 2: Utility of UAV 1 versus unit rate utility factor α for UAVs under different schemes.

one is named scheme 3 without considering the power consumption in utilities of UAVs.

Figures 2 and 3 illustrate the utility of the UAV 1 and utility of the PU changing with different unit rate utility factor α for UAVs under different schemes, respectively. As it is shown in the figures, both the utility of UAV 1 and utility of the PU increase with rising α which indicate that a higher unit rate utility factor benefits both the UAVs and PU. It is also shown that the proposed scheme outperforms the scheme 2 and scheme 3 from the perspective of power saving for UAVs. Besides, it is shown that the scheme 3 outperforms the proposed scheme and scheme 2 in terms of PU's utility. These results indicate that the core of decision-making is a tradeoff between PU and UAVs.

Similarly, Figures 4 and 5 illustrate the utility of the UAV 1 and utility of the PU versus different unit rate utility factor ξ for PU under different schemes, respectively. It is shown that both the utilities of UAV 1 and PU increase with rising ξ. It is also shown that the proposed scheme outperforms the scheme 2 and scheme 3 from the perspective of power saving

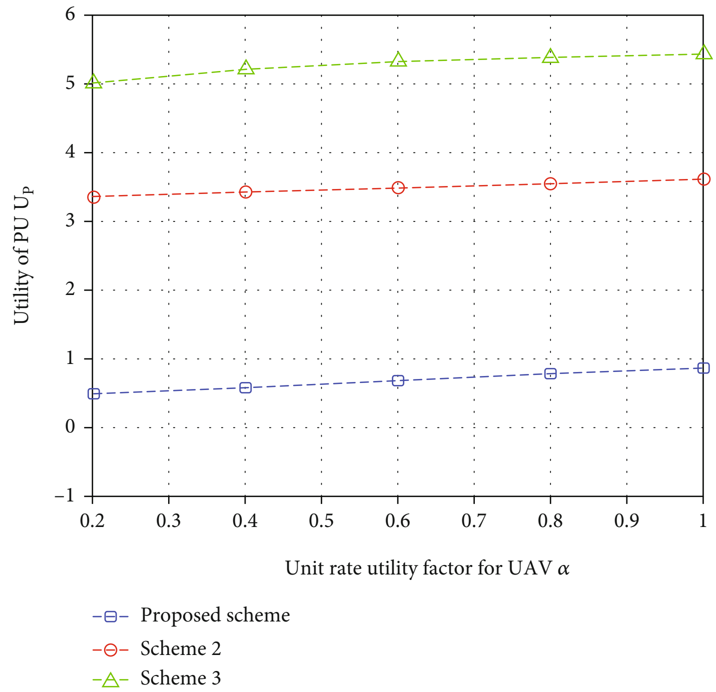

FIGURE 3: Utility of PU versus unit rate utility factor α for UAVs under different schemes.

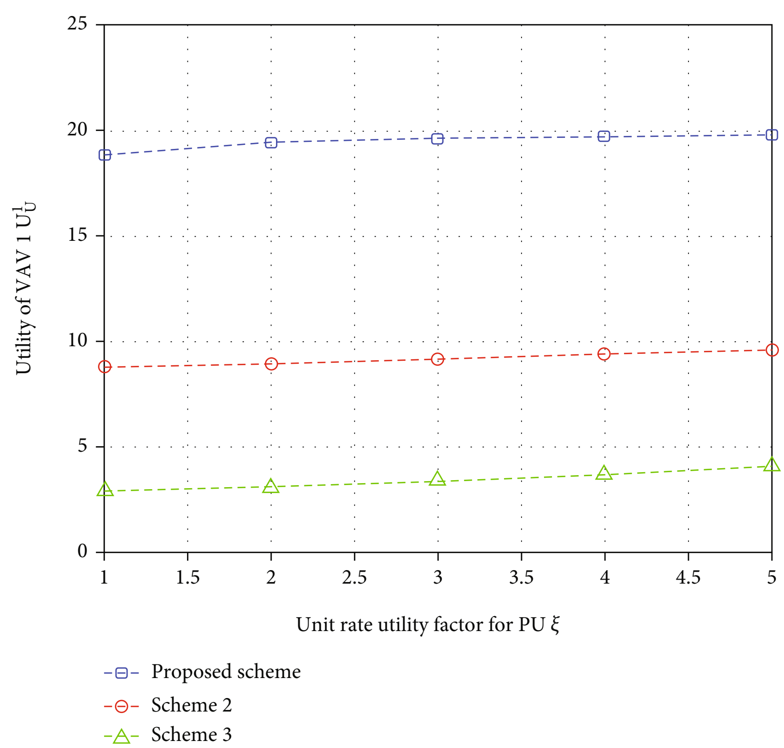

FIGURE 4: Utility of UAV 1 versus unit rate utility factor ξ for PU under different schemes.

for UAVs. Besides, it is shown that the scheme 3 outperforms the proposed scheme and scheme 2 in terms of PU's utility.

In Figures 6 and 7, the performance of the UAV 1 and PU with different energy harvesting efficiency ε under different schemes is illustrated, respectively. It is shown that the utility of PU goes up when the energy harvesting efficiency ε increases, whereas the utility of UAV 1 decreases as the ε increases. This indicates that a higher ε degrades the performance of the UAVs, while it improves the performance of

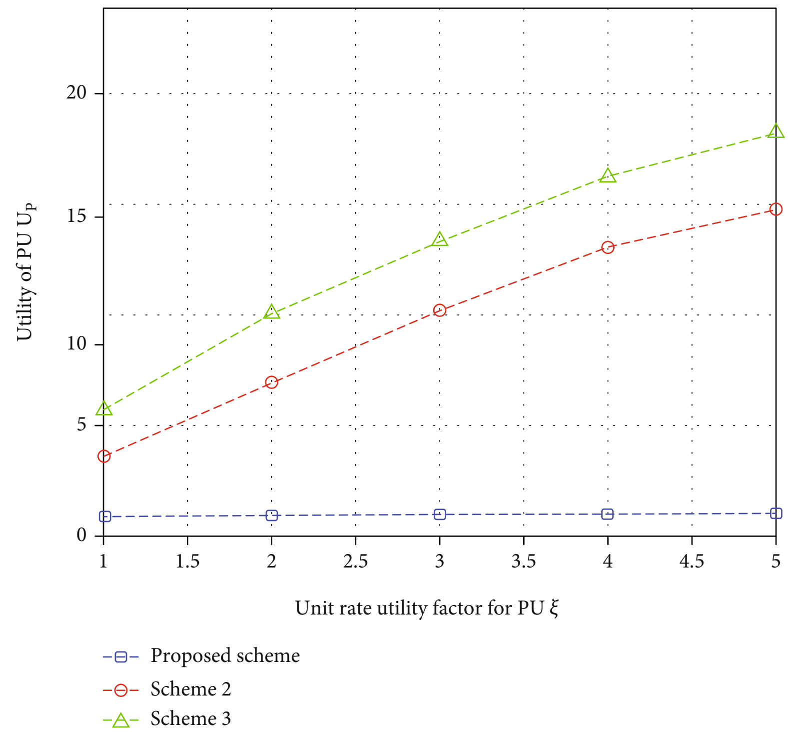

Figure 5: Utility of PU versus unit rate utility factor ξ for PU under different schemes.

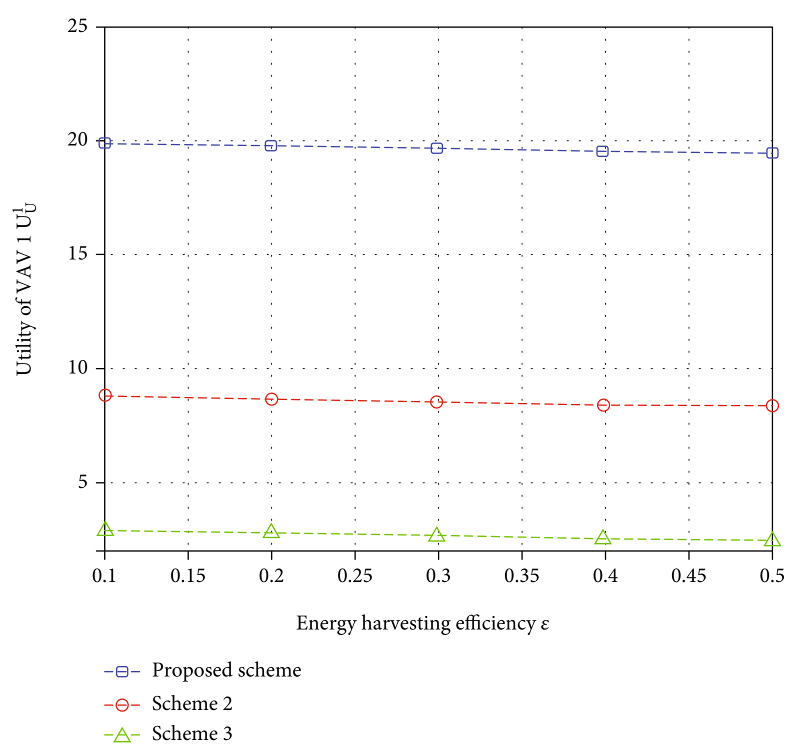

Figure 6: Utility of UAV 1 versus energy harvesting efficiency ε under different schemes.

the PU. This is because that more time is allocated to PU to achieve a higher utility of PU. It is also shown that the proposed scheme outperforms the scheme 2 and scheme 3 for UAVs. Besides, it is shown that the scheme 3 outperforms the proposed scheme and scheme 2 in terms of PU's utility.

Figures 8 and 9 show the utility of UAV 1 and the utility of PU versus the flying altitude of UAV 1, respectively. Assume that the x- and y-coordinates are fixed for both UAVs and PU. It is shown that both the utilities decrease when the flying altitude of UAV 1 increases. This is

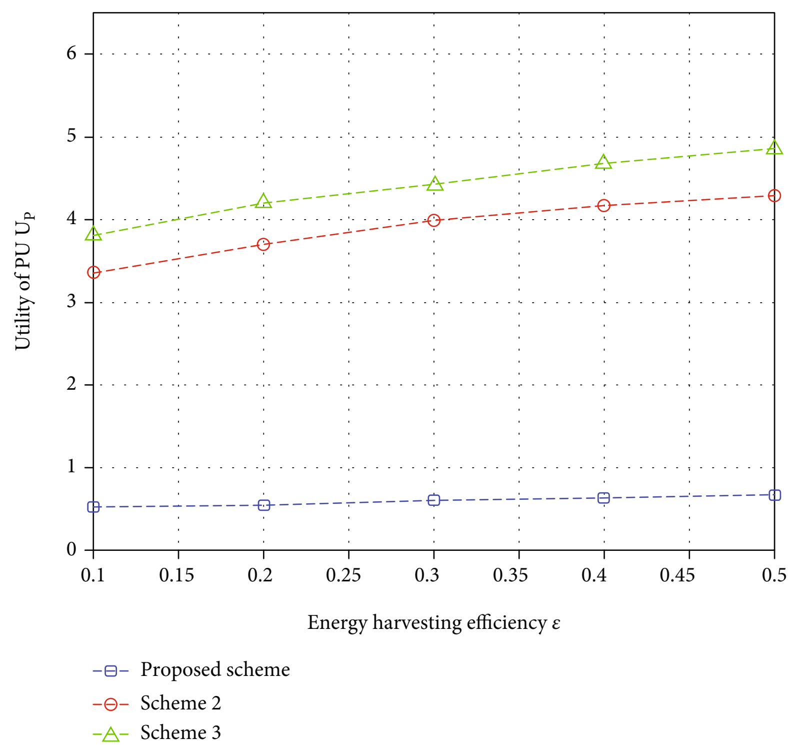

FIGURE 7: Utility of PU versus energy harvesting efficiency ε under different schemes.

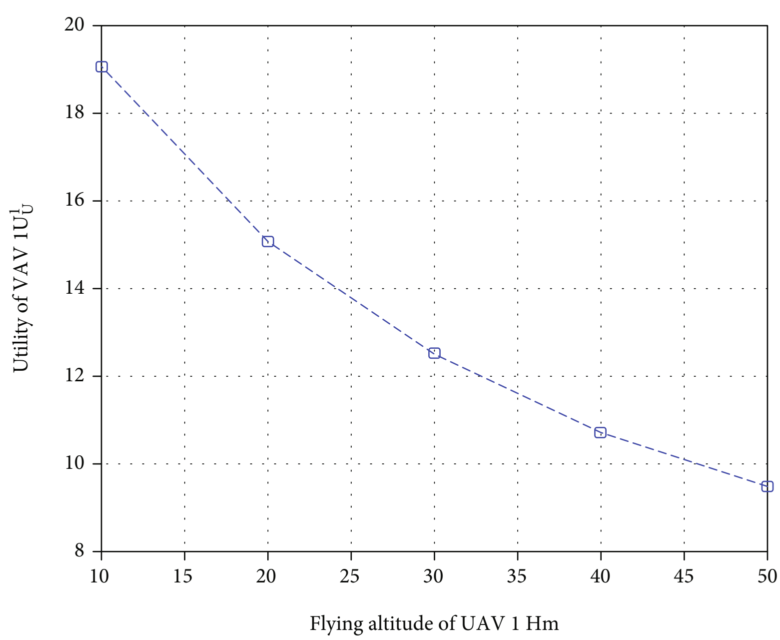

FIGURE 8: Utility of UAV 1 versus the flying altitude of UAV 1.

because that a higher flying altitude of UAV 1 decreases the channel power gains, which results in the performance degradation.

Because the utility of the proposed scheme takes the power saving into account for UAVs, the system performance is a tradeoff between PU and UAVs. Considering the endurance has already been the bottleneck for UAVs, the proposed scheme can extend the service time of UAVs while meeting the requirement of the PU.

6. Conclusions

In this paper, we investigate an UAV-based CR network with a wireless powered PU where the UAVs act as the

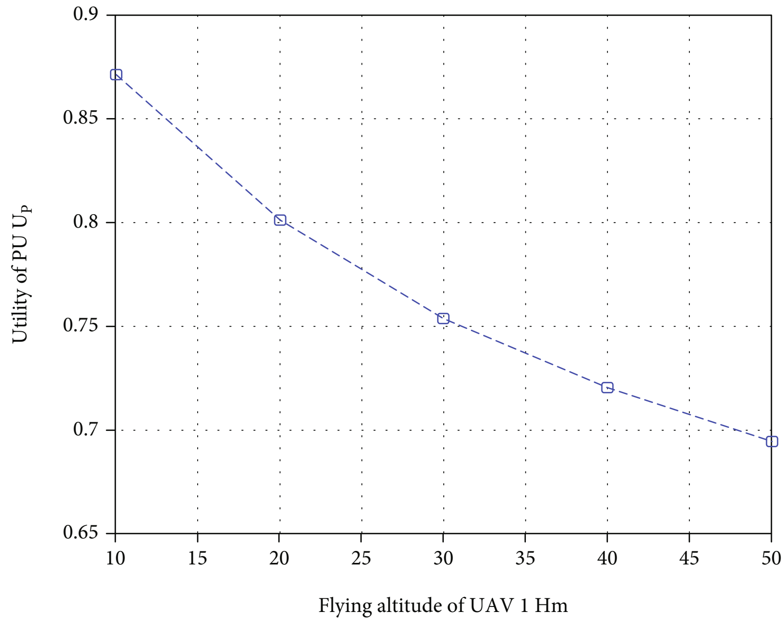

FIGURE 9: Utility of PU versus the flying altitude of UAV 1.

SUs. The PU can harvest energy from the UAVs and accumulate it for transmission. Then, we propose a price-based resource allocation scheme in cognitive UAV networks to maximize the utilities of the UAVs and the PU. Stackelberg game is adopted to analyze the interaction between the UAVs and PU, where the UAVs act as the follower and the PU acts as the leader. The whole optimization problem can be solved by an alternating iterative algorithm to achieve the Stackelberg equilibrium (SE). Different from the traditional strategies, the proposed scheme can achieve optimal utility in the view of power saving for UAVs while meeting the requirements of the PU. The simulation results validate that the proposed scheme properly balances the tradeoff between the PU and UAV performances.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interests regarding the publication of this paper.

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