

## Research Article

# Energy Efficiency Optimization of Cognitive UAV-Assisted Edge Communication for Semantic Internet of Things

Yilong Gu <sup>1</sup>, Yangchao Huang,<sup>2</sup> Hang Hu <sup>2</sup>, Weiting Gao,<sup>2</sup> and Yu Pan<sup>1</sup>

<sup>1</sup>Graduate School, Air Force Engineering University, Xi'an 710077, China

<sup>2</sup>College of Information and Navigation, Air Force Engineering University, Xi'an 710077, China

Correspondence should be addressed to Hang Hu; [xd\\_huhang@126.com](mailto:xd_huhang@126.com)

Received 17 October 2020; Revised 11 January 2021; Accepted 23 January 2021; Published 10 February 2021

Academic Editor: Chi-Hua Chen

Copyright © 2021 Yilong Gu et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

With the consolidation of the Internet of Things (IoT), the unmanned aerial vehicle- (UAV-) based IoT has attracted much attention in recent years. In the IoT, cognitive UAV can not only overcome the problem of spectrum scarcity but also improve the communication quality of the edge nodes. However, due to the generation of massive and redundant IoT data, it is difficult to realize the mutual understanding between UAV and ground nodes. At the same time, the performance of the UAV is severely limited by its battery capacity. In order to form an autonomous and energy-efficient IoT system, we investigate semantically driven cognitive UAV networks to maximize the energy efficiency (EE). The semantic device model for cognitive UAV-assisted IoT communication is constructed. And the sensing time, the flight speed of UAV, and the coverage range of UAV communication are jointly optimized to maximize the EE. Then, an efficient alternative algorithm is proposed to solve the optimization problem. Finally, we provide computer simulations to validate the proposed algorithm. The performance of the joint optimization scheme based on the proposed algorithm is compared to some benchmark schemes. And the simulation results show that the proposed scheme can obtain the optimal system parameters and can significantly improve the EE.

## 1. Introduction

An unmanned aerial vehicle (UAV), which is developed originally for military purposes, has been widely applied to the civilian domain. With the miniaturization of equipment, the continuous reduction of manufacturing cost, and the continuous improvement of communication performance, the UAV-based wireless communication has attracted much attention. In the IoT, ultrahigh data rates and reliability are critical to a lot of user connections and network sensors. In order to improve the performance of IoT networks, a massive MIMO two-way relaying system has been studied [1]. The reliability of the communication systems can be improved by Simultaneous Wireless Information and Power Transfer (SWIPT). Furthermore, with the large-scale use of mobile IoT devices, such as wearable devices, driverless cars, and intelligent terminals, the problem of making the GBS cover more communication terminals needs to be solved urgently. The coordinated direct and relay transmission (CDRT) system is investigated to extend the communication coverage

in [2]. In order to improve the spectrum efficiency, the uplink and downlink transmissions are designed jointly via network coding. Meanwhile, the advantages of the proposed scheme are verified by simulations. Meanwhile, the demand for the IoT based on UAV will be more urgent. UAV can improve the communication performance of the IoT nodes, especially in the network, whose coverage quality is poor, such as construction sites, disaster areas, highways, and narrow lanes. However, the performance of the UAV will be affected by its limited battery capacity. The method of improving the EE has become a significant direction.

The crucial drivers of IoT contain the daily addition of new devices with their own data models [3]. This leads to an enormous increase of the structured data in size and complexity. There is a demand to abstract the heterogeneity of devices so that their functions can be represented as virtual combination platforms [4–6]. A semantic IoT framework can accept heterogeneous models, which can support data sharing between devices. Thus, it needs an efficient method to update the metadata. The IoT directory sustaining semantic

description of IoT objects is proposed in [7]. Semantic description and semantic collaboration have become effective methods to realize information interaction and sharing between objects.

Usually, UAVs operate in an unlicensed spectrum. In the IoT, there are many wireless technologies, such as Wi-Fi, Bluetooth, and cellular network. The spectrum resources of the IoT become more and more scarce due to the explosive growth of wireless devices [8]. As is known to us all, a cognitive radio (CR) permits a secondary user (SU) to opportunistic access the licensed spectrum without interfering with the primary user (PU). Employing CR technology for the spectrum scarcity issue of IoT is a potential solution.

Under this background, a large number of researches on UAV-assisted IoT communication and cognitive UAV communication have been carried out. The problem of energy saving and consumption reduction of mobile IoT becomes more and more prominent. The joint optimal deployment of static ground nodes and UAVs is studied in Reference [9]. Due to the lack of dynamic research between UAVs and ground nodes, it is necessary to consider the UAV mobile relay system. Under the constraints of UAV mobility, the transmission power of the transmitter and UAV trajectory is optimized to maximize the throughput [10]. Moreover, the spectrum efficiency and energy efficiency are maximized by optimizing time allocation, flight speed, and trajectory of UAV [11]. The results show that the tradeoff between the maximum achievable spectrum efficiency and energy efficiency can be achieved by the design of the trajectory.

Aiming to improve the spectrum efficiency of IoT, it is necessary to study IoT-based CR; meanwhile, the devices in the IoT are able to sense the wireless environment [12]. The use of spectrum sharing technology in the IoT is also considered to be a mutually beneficial solution [13]. When the transmission rate of PU is lower than the requirement, a part of bandwidth is authorized to the SU to achieve the purpose of cooperative transmission. Compared with ground spectrum sensing technology, UAV spectrum sensing can obtain better sensing performance. Spectrum sensing performance can be improved by increasing the number of samples which is related to spectrum sensing time. However, improving the sensing performance may consume more sensing time and thus decrease the transmission time. It is proved that there is a sensing-throughput tradeoff in spectrum sensing of the CR, i.e., there exists an optimal sensing time that makes throughput of the CR achieve the maximal value [14]. In [15], the cooperative method based on decode-and-forward and physical-layer network coding is proposed to reduce the transmission delay of wireless sensor networks. Furthermore, the cooperative compressed spectrum sensing algorithm for UAV is proposed to improve sensing accuracy, which allows ground nodes to send compressed sensing information to UAV [16–18].

Semantic IoT devices with cognitive function can solve the problem of low spectrum efficiency by spectrum sensing [19]. UAV, as the air interface of the IoT, can effectively solve the problem of long-distance communication under the condition of energy limitation of IoT. However, there are few studies applying these two advantages of UAV to the seman-

tic IoT. This paper considers that the CR-based UAV can opportunistically use the spectrum to provide information for the remote semantic IoT devices. In order to achieve the green and autonomous IoT, the EE of the cognitive UAV system is investigated.

In this paper, the maximization of semantic IoT's EE based on cognitive UAV is studied. On the basis of building a semantic device model for cognitive UAV to assist IoT communication, we jointly optimize the UAV sensing time, UAV flight speed, and UAV communication distance to maximize the EE. We solve this problem by dividing it into three subproblems. And an efficient alternative algorithm is proposed to obtain the optimal solution. Through computer simulations, we verify the proposed scheme. It is concluded that the proposed scheme can achieve better performance compared to the benchmark schemes and can obtain the maximum EE.

The rest of this paper is organized as follows. In Section 2, we consider a cognitive fixed-wing UAV with a circular trajectory. The UAV can opportunistically access the spectrum of GBS. And the semantic device model for cognitive UAV-assisted IoT communication is constructed, which is used to establish autonomous communication links between UAV and the ground nodes farther away from the ground base station (GBS). In Section 3, an algorithm is proposed to obtain the maximal EE of UAV cognitive communication. In Section 4, the algorithm is simulated. And the comparison shows that our joint optimization scheme can significantly improve the EE. Finally, conclusions are drawn in Section 5.

## 2. System Model

We consider a UAV-assisted edge IoT model consisting of a GBS, a UAV, and a group of ground nodes, such as car nodes, smartphone nodes, and computer nodes. As a relay node, the cognitive UAV is aimed at serving the ground nodes with low communication quality due to the long distance from the GBS. At the same time, the cognitive UAV can use the spectrum of GBS to communicate with the ground nodes and transmits its own messages when the spectrum of the GBS is idle [20]. Since the battery capacity of the UAV is usually limited, we aim to maximize the energy efficiency of UAV relay communication on the basis of improving spectrum efficiency in the IoT.

The UAV flies in a circle around the GBS which is located at the center of the circular flight path. We consider that the UAVs are equipped with a Global Positioning System (GPS); thus, their geographical coordinates can be obtained. The flying speed of UAV in a circular motion is  $v$ , and the radius of the UAV flight path is  $d_u$ . The advantage of using a circular trajectory is that the UAV can not only save energy consumption greatly [21] but also provide regular communication service. When the UAV flies to position  $A$ ,  $B$ , or  $C$ , it can communicate with ground nodes in the circle  $A'$ ,  $B'$ , or  $C'$  directly below it, which is shown in Figure 1.

The association rules between UAV and ground nodes can be determined by semantic technology. In order to support the autonomous scheduling of communication, the

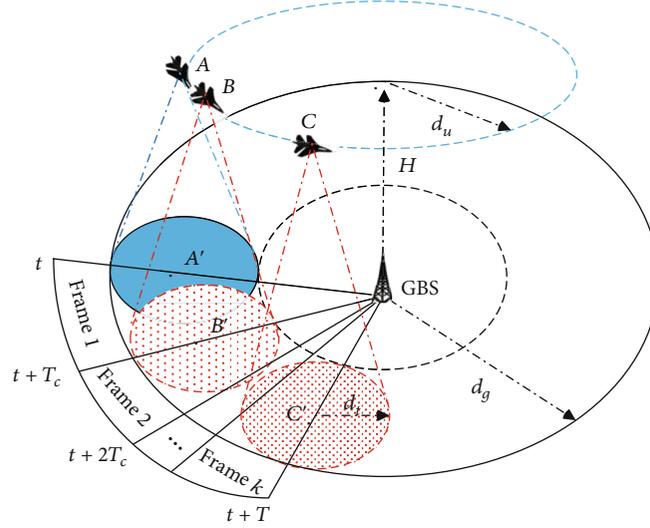


FIGURE 1: UAV-assisted edge communication system for IoT.

semantic representation model of IoT nodes is constructed from four aspects of basic equipment information, communication capability, communication state, and operation control, as shown in Figure 2.

The basic parameters are the semantic descriptions of its name, type, and technical parameters, where the location parameter represents the three-dimensional position of the node, which is needed for cognitive UAV to establish an assisted communication link. Application description describes the relevant parameter information of the node in different environments. And the communication mode, protocol, and communication coverage range of UAV are described by communication capability.

Let the task state indicate whether the node can establish the communication link. And the communication quality of IoT nodes covered by GBS is defined by coverage quality. The sensing state represents the information obtained by the UAV through environment sensing.

In order to enable UAV to adjust speed, sensing time, and communication coverage range in response to changing electromagnetic environment, we conducted a semantic model for operational control. The acquisition of ground nodes' state and control of communication link establishment are also described in the model of operating control.

Then, at a certain moment, the UAV can establish communication link with ground nodes in a circular region  $S_c$  with radius  $d_t$ .  $S_c$  is in the projection area below the UAV's flight position, as shown in Figure 3.  $d_t$  is determined by the UAV's communication range of the semantic model.

We define  $M$  as the total number of ground nodes in  $S_c$ , which are served by UAV at time  $t$ . Suppose that the ground nodes are randomly and evenly distributed in the circular area centered on PU with a radius of  $d_g$ , then we have  $d_u = d_g - d_t$ . The density of ground users is represented by  $\rho$ ; hence,  $M$  can be expressed as

$$M = \lfloor \rho \pi d_t^2 \rfloor, \quad (1)$$

where  $\lfloor x \rfloor$  denotes the largest integer no more than  $x$ .

The frame  $T_c$  is divided into the sensing slot and transmission slot. In the sensing slot, the UAV senses whether the GBS is active within time  $\tau$ . If GBS is detected inactive, the UAV opportunistically uses the primary spectrum belonging to the GBS to send information to ground nodes within transmission slot  $T_c - \tau$ .

Then, two types of channels are considered: (i) the GBS to UAV channel and (ii) the UAV to ground node channel. These channels can be assumed to be line of sight (LOS). We assume that the UAV is flying horizontally with a fixed altitude  $K$ , which meets the minimum height required to avoid the actual terrain or buildings, so that frequent adjustment of flight altitude is not required. Thus, the impact of severe ground fading on the sensing and transmission performance can be ignored. The channel power gain of the UAV to a ground node follows the free-space path loss model, which can be expressed as

$$h_t = \frac{\beta_0}{K^2 + d(t)^2}, \quad (2)$$

where  $\beta_0$  denotes the channel power at the reference distance of one meter.  $d(t)$  denotes the horizontal distance from the UAV to the ground node at a certain time  $t$ . In addition, we suppose that the Doppler effect produced by the UAV's movement is offset.

In this paper, we consider that the bandwidth of the GBS has been allocated in advance. It is assumed that the total available bandwidth provided to UAV is  $W$  in Hz. To facilitate the analysis, we use  $\rho \pi d_t^2$  as the number of ground nodes in  $S_c$ , and the bandwidth allocated to each ground node is

$$W' = \frac{W}{\rho \pi d_t^2}. \quad (3)$$

The transmission power of UAV to each ground node is defined as  $P_t$ . To guarantee the quality of the whole

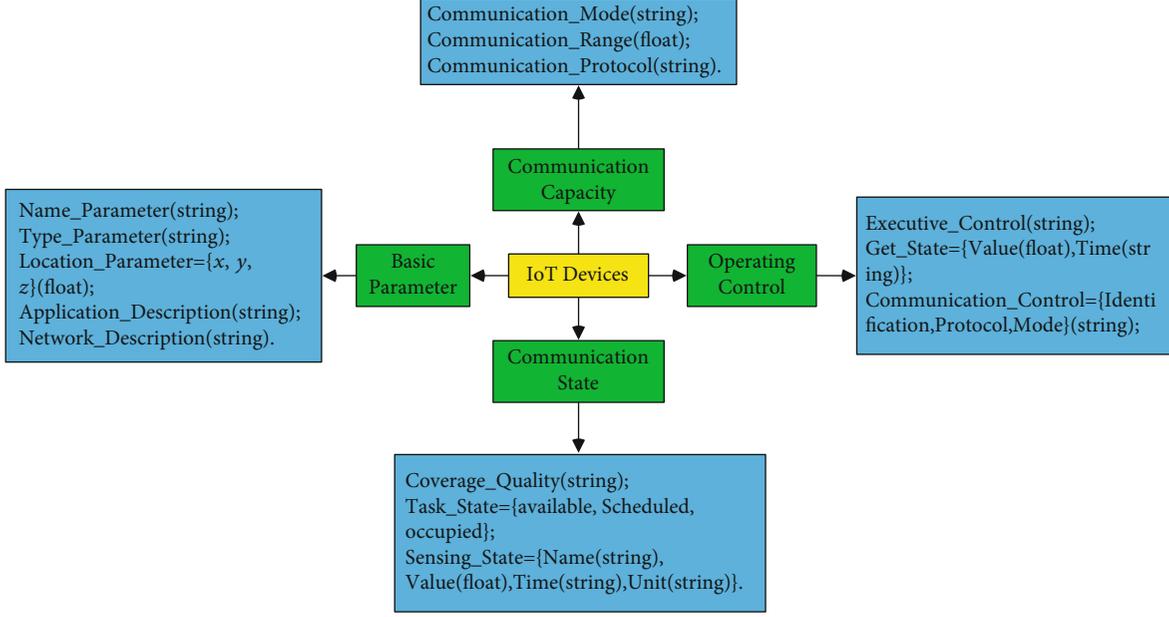


FIGURE 2: Semantic model for UAV-assisted communication in the IoT.

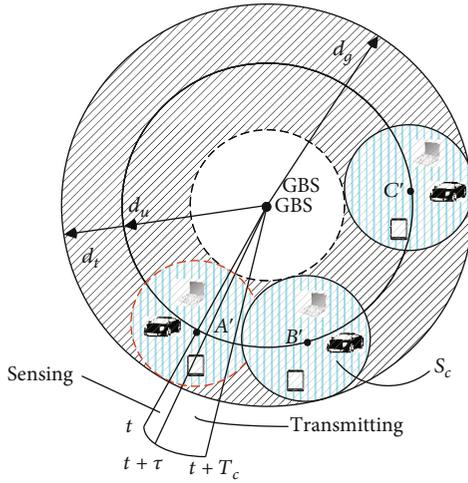


FIGURE 3: Spectrum sensing model.

communication network, we consider the worst case that the UAV communicates with the edge nodes of  $S_c$ .

Let  $C_0$  denote the transmission rate from UAV to each ground node, which can be expressed as

$$C_0 = \log_2 \left( 1 + \frac{\beta_0 P_t}{(K^2 + d_t^2) W' \sigma^2} \right), \quad (4)$$

where  $\sigma^2$  denotes the noise variance.

Next, the situation in which the UAV can use the frequency band of GBS is divided into the following two cases:

- (i) When true status of the GBS is inactive and the sensing result of the UAV shows that it is inactive, the

achievable throughput of the UAV's communication link is  $((T_c - \tau)/T_c)C_0$

- (ii) When true status of the GBS is active and the sensing result of the UAV shows that it is inactive, the achievable throughput of the UAV's communication link is  $((T_c - \tau)/T_c)C_1$

Suppose that the primary signal is a binary phase shift keying (BPSK) signal, the noise is a real-valued Gaussian variable. And the energy detection method is used to detect the GBS's status. The signal to noise ratio (SNR) received by UAV is denoted as  $\gamma$ . The false alarming probability and the detection probability are denoted as  $P_f$  and  $P_d$ , respectively. And the sampling frequency is  $f_s$ . In the practice of low SNR, in order to protect the GBS from the interference of UAV, the detection probability of target  $\bar{P}_d$  is required to be close to 1 but less than 1.

Then, for given target probabilities  $\bar{P}_d$  and  $\bar{P}_f$ ,  $P_f$  and  $P_d$  are given by [22]

$$\begin{aligned} P_f &= Q\left(\sqrt{2\gamma+1}Q^{-1}(\bar{P}_d) + \sqrt{\tau f_s \gamma}\right), \\ P_d &= Q\left(\frac{1}{\sqrt{2\gamma+1}}Q^{-1}(\bar{P}_f) + \sqrt{\tau f_s \gamma}\right), \end{aligned} \quad (5)$$

where  $Q(x)$  is the distribution function of standard Gaussian, which is given by  $Q(x) = (1/\sqrt{2\pi}) \int_x^\infty \exp(-t^2/2) dt$ .

When the frequency band  $W$  is given,  $P(H_1)$  is the active probability of GBS, and  $P(H_0)$  is the inactive probability of GBS. Therefore, the probability that the first case happens is  $(1 - P_f)P(H_0)$ , and the probability for the second case to happen is  $(1 - P_d)P(H_1)$ .

Hence, the effective throughput of the UAV communication link without active GBS is given as follows:

$$R_0 = \frac{T_c - \tau}{T_c} C_0 (1 - P_f) P(H_0). \quad (6)$$

When the GBS is inactive, the throughput is

$$R_1 = \frac{T_c - \tau}{T_c} C_1 (1 - P_d) P(H_1). \quad (7)$$

Then, the average throughput of the UAV communication link is

$$R = R_0 + R_1. \quad (8)$$

The following three cases will be considered when we analyze  $R$  in practice.

- (i) When the UAV fails to sense that the GBS is active, there is interference between UAV and GBS; hence, the value of  $C_1$  will be small, or the ground nodes may not decode the data transmitted from the UAV
- (ii) The target detection probability is usually greater than 0.9 for the SNR of -20 dB, which is in IEEE 802.22 WRAN
- (iii) The GBS's active probability  $P(H_1)$  is small enough, less than 0.3 [21], so that it is economically advisable to explore the licensed spectrum band

Based on the above analysis,  $C_1(1 - P_d)P(H_1) \ll C_0(1 - P_f)P(H_0)$ ; then, the average throughput can be approximated as

$$\tilde{R} \approx R_0 = C_0 P(H_0) \left(1 - \frac{\tau}{T_c}\right) \left(1 - Q\left(\alpha + \sqrt{\tau f_s \gamma}\right)\right), \quad (9)$$

where  $\alpha = \sqrt{2\gamma + 1} Q^{-1}(\bar{P}_d)$ .

Next, we analyze the energy consumption of UAV. The energy consumption of UAV is divided into two parts. One is the energy consumption associated with communication; the other is the energy required to maintain a fixed-wing drone flight. In practice, the power associated with communication is usually much smaller than the power needed to fly. The power needed to communicate is typically a few watts, but the UAV's propulsion power is usually hundreds of watts. Therefore, the power associated with UAV communication is ignored in this paper.

For constant speed circular flight, we have  $\|v(t)\| = v$  and  $a(t)^T v(t) = 0$ . Particularly,  $a(t)$  denotes the centripetal acceleration of UAV, whose direction must be perpendicular to the direction of velocity to ensure the constant speed. It can be seen from [23] that the power consumption of the UAV's steady circular flight is further derived:

$$\Xi = \left(c_1 + \frac{c_2}{g^2 d_u^2}\right) v^3 + \frac{c_2}{v}, \quad (10)$$

where  $g$  is the gravitational acceleration with normal value 9.8 m/s<sup>2</sup>.  $c_1$  and  $c_2$  are determined by the weight of the aircraft, wing area, air density, and so on. This model conforms to the known classical aircraft power consumption model of aerodynamics theory.

According to formulas (9) and (10), the energy efficiency of IoT based on cognitive UAV can be expressed as

$$\eta = \frac{\tilde{R}}{\Xi} = \frac{P(H_0)(1 - \tau/T_c) \left(1 - Q\left(\alpha + \sqrt{\tau f_s \gamma}\right)\right) \log_2(1 + \beta_0 P_t \rho \pi d_t^2 / (K^2 + d_t^2)) W \sigma^2}{\left(c_1 + c_2/g^2(d_g - d_t)^2\right) v^3 + c_2/v}. \quad (11)$$

It is a function with  $\tau, d_t, v$  as variables.

### 3. Solutions of the Optimization Problem

Our goal is to maximize the energy efficiency of the IoT based on cognitive UAV relay communication by optimizing UAV flying speed  $v$ , the sensing slot duration  $\tau$ , and the communication distance threshold  $d_t$ . This optimization problem can be formulated as

$$\begin{aligned} \text{(OP): } & \max_{\tau, v, d_t} \eta, \\ & 0 \leq \tau \leq T_c, \\ & 0 \leq v \leq v_{\max}, \\ & 0 \leq d_t \leq d_g. \end{aligned} \quad (12)$$

In the objective function,  $\tau$  determines the molecular part and  $v$  influences the denominator part. Then, we can take into account that optimization of objective function can be solved by dividing the problem OP into three subproblems.

*3.1. Optimization of  $v$  with Fixed  $\tau$  and  $d_t$ .* The first subproblem OP<sub>1</sub> can be worked out by solving the optimal  $v$  to minimize the energy consumption of UAV with fixed  $\tau$  and  $d_t$ :

$$\begin{aligned} \text{(OP}_1\text{): } & \min_v P, \\ & 0 \leq v \leq v_{\max}. \end{aligned} \quad (13)$$

In order to obtain the optimal flight speed of UAV, we take its first derivative of the  $\Xi$  to analyze the monotonicity:

$$\frac{\partial \Xi}{\partial v} = 3v^2 \left( c_1 + \frac{c_2}{g^2 d_u^2} \right) - \frac{c_2}{v^2}. \quad (14)$$

Then, we have  $\lim_{v \rightarrow \infty} \partial \Xi / \partial v = +\infty$  and  $\lim_{v \rightarrow 0} \partial \Xi / \partial v = -\infty$ . Next, the second derivative of  $\Xi$  with respect in  $v$  is given as follows:

$$\frac{\partial^2 \Xi}{\partial v^2} = 6v \left( c_1 + \frac{c_2}{g^2 d_u^2} \right) + \frac{2c_2}{v^3} > 0. \quad (15)$$

As the result shown in equation (15), we can know that  $\Xi$  is convex in  $v$ . By solving equation (14) equal to 0, we have

$$v_0 = \sqrt[4]{\frac{c_2}{3c_1 + 3c_2/g^2(d_g - d_t)^2}}. \quad (16)$$

Obviously, the function  $\Xi$  decreases monotonically in the interval  $(0, v_0)$  and increases monotonically when  $v$  is larger than  $v_0$ . Define the optimal  $v$  as  $v^*$ . Then, if  $v_0 < v_{\max}$ , we have  $v^* = v_0$ , and if  $v_0 > v_{\max}$ , we have  $v^* = v_{\max}$ . Hence, the minimum energy consumption of UAV is taken as  $v = v^*$ , when  $\tau$  and  $d_t$  are fixed.

**3.2. Optimization of  $\tau$  with Fixed  $v$  and  $d_t$ .** The second subproblem is to achieve the maximal average throughput when  $v$  and  $d_t$  are fixed:

$$\begin{aligned} (\text{OP}_2): \quad & \max_{\tau} \tilde{R}, \\ & 0 \leq \tau \leq T_c. \end{aligned} \quad (17)$$

Therefore, we can obtain that the average throughput is a function of  $\tau$ . In order to prove that the optimal  $\tau$  exists, we take the first derivative of  $\tilde{R}$ :

$$\begin{aligned} \frac{\partial \tilde{R}}{\partial \tau} = C_0 P(H_0) & \left[ \frac{\gamma \sqrt{f_s} (1 - \tau/T_c)}{2\sqrt{2\pi\tau}} \exp \left( -\frac{(\alpha + \sqrt{\tau f_s} \gamma)^2}{2} \right) \right. \\ & \left. - \frac{1}{T_c} + \frac{1}{T_c} Q(\alpha + \sqrt{\tau f_s} \gamma) \right]. \end{aligned} \quad (18)$$

Then,

$$\lim_{\tau \rightarrow 0} \frac{\partial \tilde{R}}{\partial \tau} = +\infty. \quad (19)$$

Since  $Q(x)$  is decreasing with upper boundary 1,  $Q(\alpha + \sqrt{T_c f_s} \gamma) - 1 < 0$ , we have

$$\lim_{\tau \rightarrow T_c} \frac{\partial \tilde{R}}{\partial \tau} = \frac{1}{T_c} \left( Q(\alpha + \sqrt{T_c f_s} \gamma) - 1 \right) C_0 P(H_0) < 0, \quad (20)$$

and the second derivative of  $\tilde{R}$  is as follows:

$$\begin{aligned} \frac{\partial^2 \tilde{R}}{\partial \tau^2} & \frac{1}{C_0 P(H_0)} = \frac{-\gamma \sqrt{f_s} / T_c + \gamma \sqrt{f_s} (\alpha + \gamma \sqrt{\tau f_s}) / 2\sqrt{\tau}}{8\pi\tau} 2\sqrt{2\pi\tau} \exp \\ & \cdot \left( -\frac{(\alpha + \gamma \sqrt{\tau f_s})^2}{2} \right) - \gamma \left( 1 - \frac{\tau}{T_c} \right) \sqrt{\frac{2\pi f_s}{\tau}} \exp \\ & \cdot \left( -\frac{(\alpha + \gamma \sqrt{\tau f_s})^2}{2} \right) - \frac{1}{2T_c} \sqrt{\frac{f_s}{2\pi\tau}} \exp \left( -\frac{\gamma^2 f_s \tau}{2} \right) < 0. \end{aligned} \quad (21)$$

Equation (21) shows that  $\partial \tilde{R} / \partial \tau$  is monotonic decline. Equations (19) and (20) show that  $\tilde{R}(\tau)$  increases when the sensing time approaches 0, and  $\tilde{R}(\tau)$  decreases when the sensing time approaches  $T_c$ . Therefore, define the optimal  $\tau$  as  $\tau^*$ , and it is reliable that  $\tau^*$  exists in the interval  $(0, T_c)$ . For any given  $d_t$  and  $v$ , the Golden section method is used to obtain the optimal sensing time  $\tau^*$ .

**3.3. Optimization of  $d_t$  with Fixed  $\tau$  and  $v$ .** The last subproblem  $\text{OP}_3$  is given by maximizing the energy efficiency with fixed  $\tau$  and  $v$ :

$$\begin{aligned} (\text{OP}_3): \quad & \max_{d_t} \eta, \\ & 0 \leq d_t \leq d_g. \end{aligned} \quad (22)$$

Notice that we need to adjust the value of  $d_t$  to achieve the maximum energy efficiency by tradeoff between maximum throughput and minimum energy consumption.

For any fixed radius  $d_t$ , the optimal speed  $v^*$  is obtained by solving  $P_1$ . And we notice that  $d_t$  and  $\tau$  are two independent parameters. Thus, the multivariate function is reduced to a function with  $d_t$  as a single variable. We have

$$\begin{aligned} \frac{\partial \eta}{\partial d_t} = \frac{P(H_0)(1 - \tau/T_c) \left( 1 - Q(\alpha + \sqrt{\tau f_s} \gamma) \right)}{\Xi^2} \\ \cdot \left[ \frac{2K^2 \Xi}{\ln 2 d_t (K^2 + d_t^2)} - \frac{C_0 2c_2 v^3}{g^2 (d_g - d_t)^3} \right]. \end{aligned} \quad (23)$$

Define

$$G = \frac{2K^2 \Xi}{d_t (K^2 + d_t^2) \ln 2} - \frac{C_0 2c_2 v^3}{g^2 (d_g - d_t)^3}, \quad (24)$$

when  $d_t$  is close to 0,  $\Xi$  is close to a positive constant and  $C_0$  is close to 0. Then, we have

$$\lim_{d_t \rightarrow 0} G = +\infty. \quad (25)$$

**1: Input**  
 $\rho, W, K, P_t, T_c, \sigma, v_{\max}$ .  
**2:** Let  $d_t = d_g$  and  $d_t' = d_g - \Delta$  ( $\Delta$  is a number small enough).  
**3:** According to algorithm 2 to obtain  $\tau^*$ .  
**4:** Use  $d_t$  and  $d_t'$  obtain the  $v_0$  and  $v_0'$  according to equation (16).  
**5:** If  $v_0 < v_{\max}$   
 $v^* = v_0$   
else  
 $v^* = v_{\max}$ .  
**6:** If  $\eta(d_t, v^*, \tau^*) < \eta'(d_t', v^*, \tau^*)$ , let  $d_t = d_t', d_t' = d_t - \Delta$ .  
**7:** Repeat step 3 and 4 calculate until  $\eta(d_t, v^*, \tau^*) > \eta'(d_t', v^*, \tau^*)$ .  
**8:** Record  $d_t^* = d_t$  and  $\eta^* = \eta$ .  
**9: Output**  
 $(d_t^*, v^*, \tau^*, \eta^*)$

ALGORITHM 1: Algorithm for energy efficiency maximization problem.

**1:** Initialize interval  $(0, T_c)$  as  $(a_1, b_1)$ , tolerance level  $\mu$  and the iterative number  $N$ .  
**2:** Calculate the result of  $\tilde{R}$  according to the equation (9).  
**3:**  $k=1, \lambda_1 = a_1 + 0.382(b_1 - a_1), \mu_1 = a_1 + 0.618(b_1 - a_1)$ .  
**4:** While  $b_k - a_k > \mu$  or  $k < N$   
if  $\tilde{R}(\lambda_k) < \tilde{R}(\mu_k)$   
 $a_{k+1} = \lambda_k, b_{k+1} = b_k$   
 $\lambda_{k+1} = a_{k+1} + 0.382(b_{k+1} - a_{k+1})$   
else  
 $a_{k+1} = a_k, b_{k+1} = \mu_k$   
 $\mu_{k+1} = a_{k+1} + 0.618(b_{k+1} - a_{k+1})$   
 $k = k + 1$   
end while  
 $\tau^* = (b_k + a_k)/2$   
**5:** Update  $d_t$  to satisfy the constraints (14), repeat 3, 4 and 5 steps to get  $\tau^*$ .

ALGORITHM 2: Subalgorithm for Algorithm 1.

Let

$$G_1 = \frac{2K^2(c_1 v^3 + c_2 v)}{d_t(K^2 + d_t^2) \ln 2}, \quad (26)$$

$$G_2 = \frac{2c_2 v^3 [K^2(d_g - d_t) - C_0 d_t(K^2 + d_t^2) \ln 2]}{d_t(K^2 + d_t^2) g^2 (d_g - d_t)^3 \ln 2};$$

equation (24) can be written as

$$G = G_1 + G_2. \quad (27)$$

Since  $\lim_{d_t \rightarrow d_g} G_2 = -\infty$  and  $\lim_{d_t \rightarrow d_g} G_1 = 2H^2(c_1 v^3 + c_2 v)/d_g(K^2 + d_g^2) \ln 2$ , thus

$$\lim_{d_t \rightarrow d_g} G = -\infty. \quad (28)$$

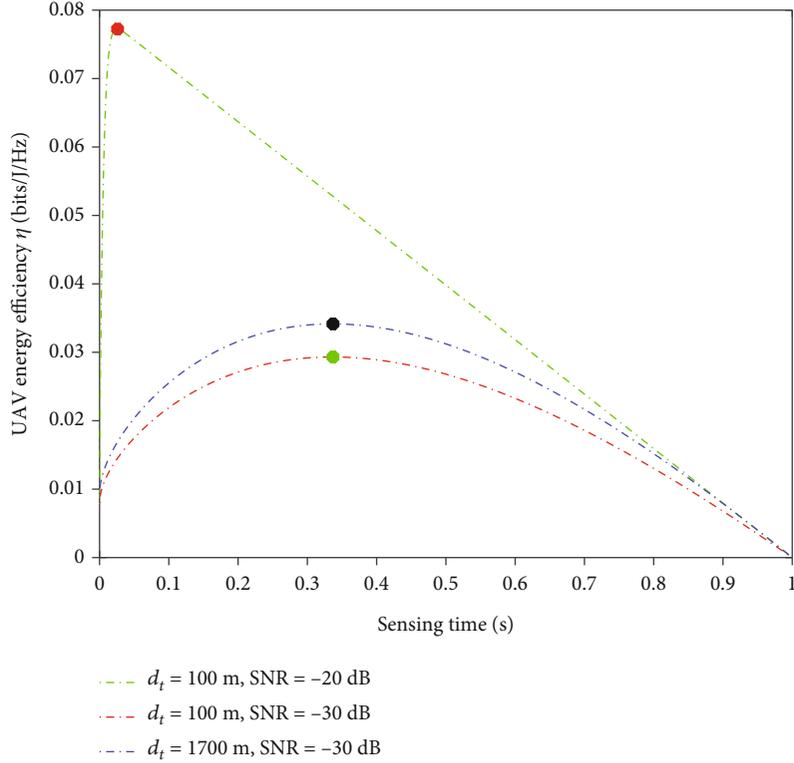
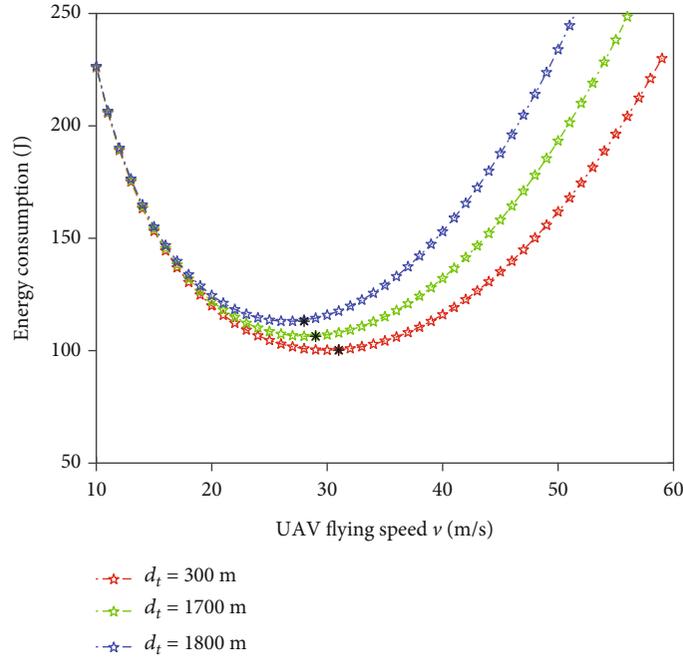
Obviously,  $\Xi^2 > 0$ . Therefore,  $\lim_{d_t \rightarrow 0} \partial \eta / \partial d_t = +\infty$  and  $\lim_{d_t \rightarrow d_g} \partial \eta / \partial d_t = -\infty$ . It is shown that  $\eta$  increases when  $d_t$

TABLE 1: Parameters in numerical analysis.

Parameter	Value	Parameter	Value
$P(H_0)$	0.8	$\rho$ (1/m <sup>2</sup> )	0.001
$d_g$ (m)	2000	$\sigma^2$ (dBm)	-150
$T_c$ (s)	1	$K$ (m)	200
$P_t$ (w)	1	$\beta_0$ (dB)	-50
$W$ (MHz)	6	$c_1$	$9.26 \times 10^{-4}$
$c_2$	2250	$\gamma$ (dB)	-20
$g$ (m/s <sup>2</sup> )	9.8		

is small and decreases when  $d_t$  approaches  $d_g$ . By calculating the limit of  $\eta$ , we have  $\lim_{d_t \rightarrow 0} \eta = 0$  and  $\lim_{d_t \rightarrow d_g} \eta = 0$ .

Hence, there is a maximum point of  $\eta(d_t)$  within interval  $(0, d_g)$ . Define this optimal  $d_t$  as  $d_t^*$ , which can be efficiently found numerically by iterative search. And the maximum energy efficiency is obtained when  $d_t = d_t^*$ . After obtaining

FIGURE 4: Energy efficiency vs. sensing time:  $T_c = 1$  s.FIGURE 5: UAV energy consumption vs. UAV speed under different  $d_t$ .

the optimal sensing time and optimal speed, exhaustive search is used to obtain optimal  $d_t$ . Then, the algorithm to solve the problem OP is shown as follows.

For each given  $d_t$ , the computation complexity of Algorithm 2 is  $\beta$ , where  $\beta = \lceil \log_2 T_c / \mu \rceil$  is the number of

iterations that the Golden section method takes to terminate and  $\lceil (\cdot) \rceil$  represents the smallest integer not less than  $(\cdot)$  [24]. The computation complexity to find optimal  $d_t$  is  $\theta$ , where  $\theta = d_g / \Delta$ . Therefore, the overall complexity of Algorithm 1 is  $\beta\theta$ .

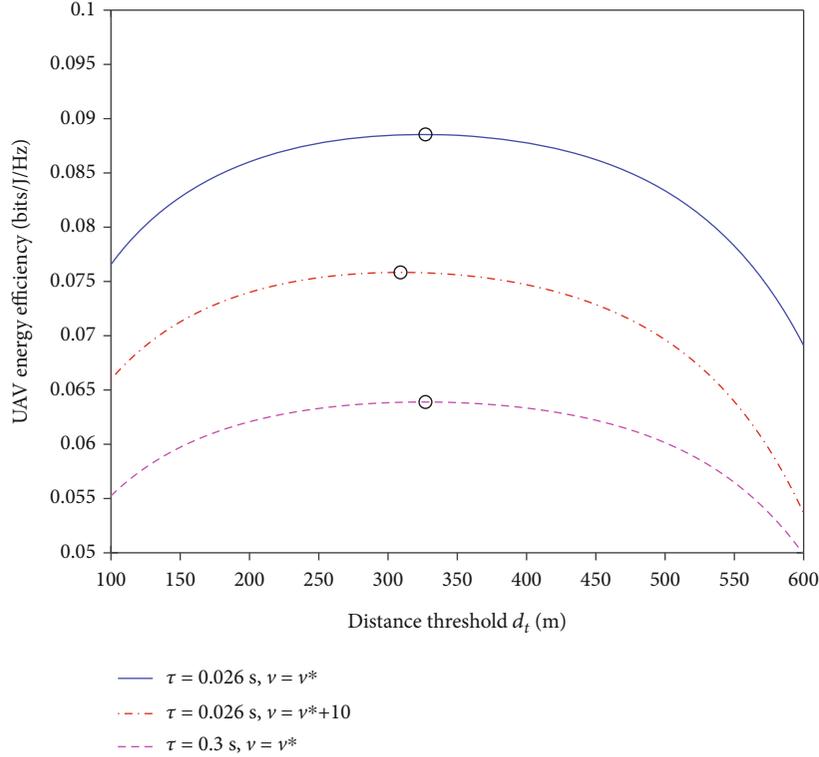
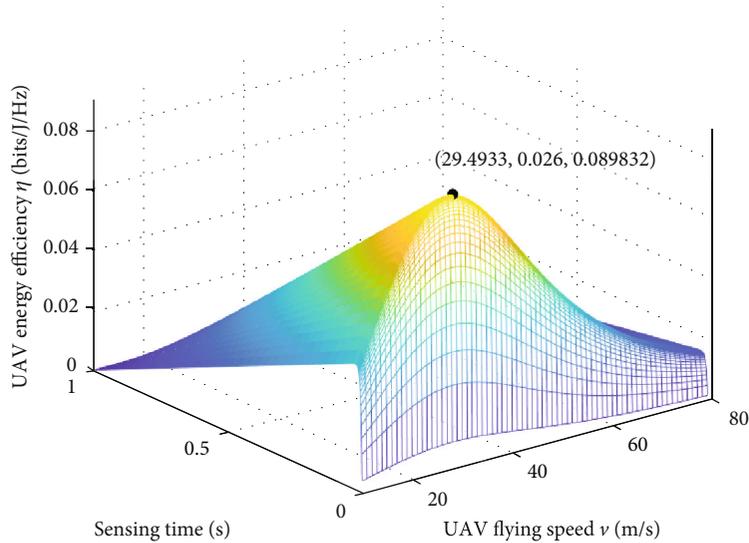


FIGURE 6: UAV energy efficiency vs. distance threshold.


 FIGURE 7: Three-dimensional map of  $\eta$  as a function of  $v$  and  $\tau$ :  $d_t = 300 \text{ m}$ .

#### 4. Numerical Results

In this section, we verify the performance of our proposed design through simulations. We set the speed of the UAV between 10 and 80. Choose  $\bar{P}_d = 0.9$ , which is in IEEE802.22 WRAN. Suppose that the central frequency of ground base station is 2.4 GHz. The specific setting of remaining parameters is shown in Table 1.

Figure 4 shows that the energy efficiency varies with the sensing time  $\tau$ . We can intuitively see that when  $d_t$  is set to

a fixed value, such as  $d_t = 100$  and  $d_t = 1700$ , there is an optimal  $\tau$  to maximize the EE  $\eta$ . It can be seen that the value of  $d_t$  can determine the value of  $\eta$ , which means  $\eta$  can be affected by the semantic description of UAV's communication coverage range. Moreover, in the case of the same  $d_t$ ,  $\tau^*$  under the condition of low receiving SNR is longer than  $\tau^*$  when receiving SNR is high, which means that it needs longer sensing time to improve the detection probability. Therefore, it is effective to set  $\tau = \tau^*$  in  $T_c$  to improve the EE.

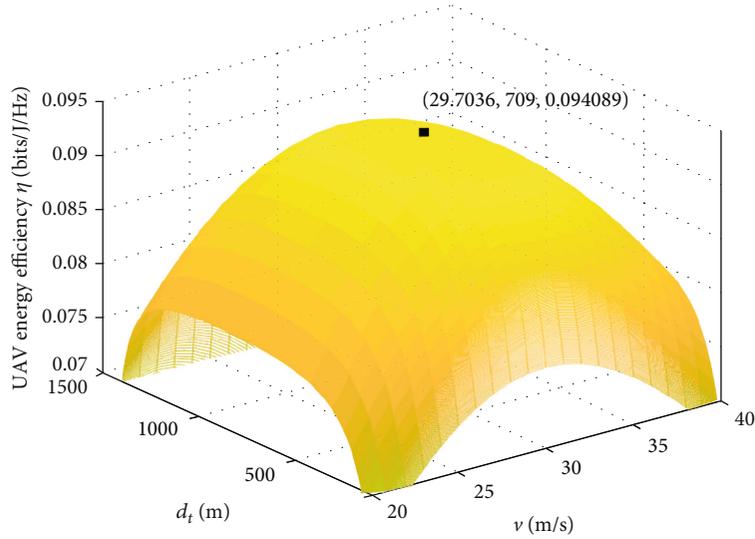


FIGURE 8: Three-dimensional map of  $\eta$  as a function of  $v$  and  $d_t$ .

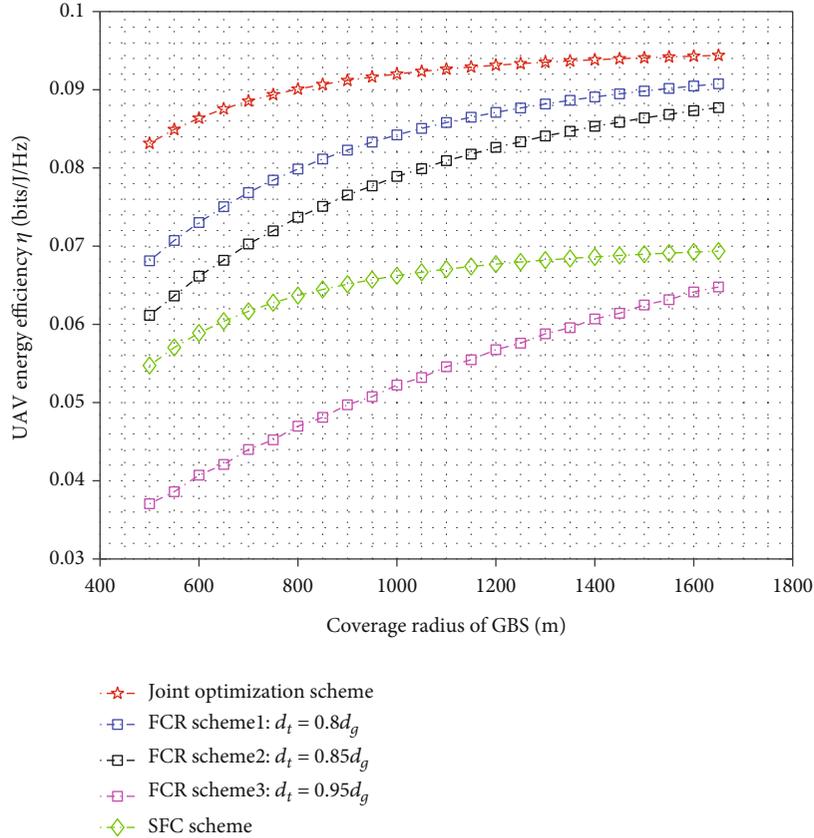


FIGURE 9: Comparison to FCR scheme and SFC scheme.

Figure 5 plots how energy consumption changes as a function of the UAV flying speed, which are under three different  $d_t$ . It shows that the energy consumption drops sharply when the speed is between 10 and 20 and increases sharply when the speed is greater than 40. Obviously with the increase of speed, the time of UAV flying over the same distance will be reduced, so it is reasonable to reduce the

energy consumption of UAV. However, the increase of UAV speed is bound to be accompanied by the increase of energy consumption. Hence, it is necessary to set a suitable value of  $v$ .

From Figure 5, we also notice that the energy consumption increases with the increase of  $d_t$ . From Figure 4, we get that  $d_t$  also affects throughput; aiming to maximize EE,  $d_t$

must be set reasonably. Therefore, we simulate the EE curves with  $d_t$ , as shown in Figure 6. It can be seen that the maximum  $\eta$  can be achieved if the  $d_t$  is set properly, when  $\nu$  and  $\tau$  are fixed. As can be seen from Figure 2,  $\tau^*$  is equal to 0.026 when the received SNR is -20 dB. It is obvious from Figure 6 that if the sensing time is equal,  $\eta$  is better when  $\nu = \nu^*$ . And if the flying speed is equal,  $\eta$  is better when  $\tau = \tau^*$ .

When communication distance threshold  $d_t = 300$  m, Figure 7 shows the effects of  $\tau$  and  $\nu$  on  $\eta$ . It indicates that there exists an optimal speed  $\nu^* \approx 29$  (m/s) and  $\tau^* = 0.026$  (s), which maximizes  $\eta$  and reaches  $\eta \approx 0.08$  (bits/J/Hz). At the same time, Figure 7 also shows that there is an optimal point to maximize  $\eta$ ; it means that there is an optimal cognitive communication scheme for UAV to obtain higher energy efficiency in the IoT. In addition, we can observe from Figures 7 and 8 that a slice parallel to the  $x$ -axis shows how the EE changes with  $\nu$ ; the slice parallel to the  $y$ -axis in Figures 7 and 8, respectively, shows that EE varies with  $\tau$  and  $d_t$ , which are consistent with the above analysis results.

Figure 9 shows a comparison between the proposed scheme and other two schemes. In the fixed communication range (FCR) scheme, the communication radius of UAV is a fixed value which can achieve higher throughput. The shortest flight cycle (SFC) scheme requires the UAV to fly at maximum speed. In this scheme, the time of energy consumption is reduced as much as possible. It can be seen that the energy efficiency decreases more and more sharply as  $d_t$  approaches the value of  $d_g$  in the FCR scheme. From Section 3, it is concluded that the average throughput will increase with the increase of  $d_t$ . Thus, for the same coverage radius of GBS, the joint optimization scheme obtains lower throughput. However, the energy efficiency of the proposed scheme is much better than FCR and SFC schemes. The result also indicates that the optimal energy efficiency can be obtained by applying the joint optimization scheme to the IoT with different parameters.

## 5. Conclusions

Based on the consideration of improving spectrum efficiency in semantic IoT, this paper mainly studies the process of UAV opportunity using the spectrum of GBS to communicate with edge nodes. A semantic device model for cognitive UAV-assisted IoT communication is constructed to ensure the automation of the IoT system. Aiming to solve the problem of UAV's limited energy supply, we propose a joint optimization algorithm to maximize the communication energy efficiency of UAV under certain constraints. In order to understand the model better, the experimental simulations are carried out. The simulation results are consistent with the theoretical analysis. It is also shown that the maximum energy efficiency for cognitive UAV in IoT can be obtained by the proposed algorithm. At the same time, the UAV's communication coverage range  $d_t$  of the semantic model will greatly influence the energy efficiency. And the performance of the joint optimization scheme is better than the fixed trajectory flight scheme with higher throughput.

## Data Availability

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

## Conflicts of Interest

There is no conflict of interest regarding the publication of this paper.

## Acknowledgments

This work is supported in part by the National Natural Science Foundation of China under grant 61901509, in part by the Natural Science Foundation of Shaanxi Province of China under grant no. 2018JM6098, in part by the Research Foundation for Talented Scholars of Xijing University under grant no. XJ17B06, and in part by the President Foundation of Air Force Engineering University under grant XZJK2019033.

## References

- [1] J. Wang, G. Wang, B. Li, H. Yang, and A. Schmeink, "Massive MIMO two-way relaying systems with SWIPT in IoT networks," *IEEE Internet of Things Journal*, 2020.
- [2] Y. Xu, B. Li, N. Zhao, Y. Chen, and X. Wang, "Coordinated direct and relay transmission with NOMA and network coding in Nakagami-m fading channels," *IEEE Transactions on Communications*, vol. 69, no. 1, pp. 207–222, 2021.
- [3] A. Palavalli, D. Karri, and S. Pasupuleti, "Semantic Internet of Things," in *2016 IEEE Tenth International Conference on Semantic Computing*, pp. 91–95, Laguna Hills, CA, USA, February 2016.
- [4] J. Kiljander, A. D'elia, F. Morandi et al., "Semantic interoperability architecture for pervasive computing and Internet of Things," *IEEE Access*, vol. 2, pp. 856–873, 2014.
- [5] G. Xiao, J. Guo, L. D. Xu, and Z. Gong, "User interoperability with heterogeneous IoT devices through transformation," *IEEE Transactions on Industrial Informatics*, vol. 10, no. 2, pp. 1486–1496, 2014.
- [6] J. Takalo-Mattila, J. Kiljander, F. Pramudianto, and E. Ferrera, "Architecture for mixed criticality resource management in Internet of Things," in *Proceedings of 2014 TRON Symposium (TRONSHOW)*, pp. 1–9, Tokyo, Japan, December 2014.
- [7] S. Chun, S. Seo, B. Oh, and K. Lee, "Semantic description, discovery and integration for the Internet of Things," in *Proceedings of the 2015 IEEE 9th International Conference on Semantic Computing*, pp. 272–275, Anaheim, CA, USA, February 2015.
- [8] B. Li, C. Chen, R. Zhang, H. Jiang, and X. Guo, "The energy-efficient UAV-based BS coverage in air-to-ground communications," in *2018 IEEE 10th Sensor Array and Multichannel Signal Processing Workshop (SAM)*, pp. 578–581, Sheffield, UK, July 2018.
- [9] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Optimal transport theory for power-efficient deployment of unmanned aerial vehicles," in *2016 IEEE International Conference on Communications*, pp. 1–6, Kuala Lumpur, Malaysia, May 2016.

- [10] Y. Zeng, R. Zhang, and T. J. Lim, "Throughput maximization for UAV-enabled mobile relaying systems," *IEEE Transactions on Communications*, vol. 64, no. 12, pp. 4983–4996, 2016.
- [11] J. Zhang, Y. Zeng, and R. Zhang, "Spectrum and energy efficiency maximization in UAV-enabled mobile relaying," in *2017 IEEE International Conference on Communications*, pp. 1–6, Paris, France, May 2017.
- [12] A. Athar, M. H. Rehmani, and A. Rachedi, "When cognitive radio meets the Internet of Things?," in *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*, pp. 469–474, Paphos, Cyprus, September 2016.
- [13] B. Zhang and K. Chen, "Selective spectrum leasing in internet of things via Nash bargaining solutions," in *2012 IEEE 2nd International Conference on Cloud Computing and Intelligence Systems*, pp. 841–845, Hangzhou, China, October–November 2012.
- [14] X. Liu, M. Guan, X. Zhang, and H. Ding, "Spectrum sensing optimization in an UAV-based cognitive radio," *IEEE Access*, vol. 6, pp. 44002–44009, 2018.
- [15] B. Li, J. Yang, H. Yang, G. Liu, R. Ma, and X. Peng, "Decode-and-forward cooperative transmission in wireless sensor networks based on physical-layer network coding," *Wireless Networks*, 2019.
- [16] N. Zhao, F. Cheng, F. R. Yu et al., "Caching UAV assisted secure transmission in hyper-dense networks based on interference alignment," *IEEE Transactions on Communications*, vol. 66, no. 5, pp. 2281–2294, 2018.
- [17] F. Cheng, S. Zhang, Z. Li et al., "UAV trajectory optimization for data offloading at the edge of multiple cells," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 6732–6736, 2018.
- [18] H. C. Chen, H. Kung, D. Vlah, D. Hague, M. Muccio, and B. Poland, "Collaborative compressive spectrum sensing in a UAV environment," in *2011 - MILCOM 2011 Military Communications Conference*, Baltimore, MD, USA, November 2011.
- [19] P. Rawat, K. D. Singh, and J. M. Bonnin, "Cognitive radio for M2M and internet of things: a survey," *Computer Communications*, vol. 94, pp. 1–29, 2016.
- [20] Y. Gao, H. Tang, B. Li, and X. Yuan, "Robust trajectory and power control for cognitive UAV secrecy communication," *IEEE Access*, vol. 8, no. 6, pp. 49338–49352, 2020.
- [21] Y.-C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, "Sensing-throughput tradeoff for cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 7, no. 4, pp. 1326–1337, 2008.
- [22] H. Hu, Y. Huang, X. Da, L. Ni, and Y. Pan, "Optimization of energy management for UAV-enabled cognitive radio," *IEEE Wireless Communications Letters*, vol. 9, no. 9, pp. 1505–1508, 2020.
- [23] Y. Zeng and R. Zhang, "Energy-efficient UAV communication with trajectory optimization," *IEEE Transactions on Wireless Communications*, vol. 16, no. 6, pp. 3747–3760, 2017.
- [24] S. Boyd and L. Vandenberghe, *Convex Optimization*, Cambridge University Press, 2013.