Spectrum- and Energy- Efficiency Analysis Under Sensing Delay Constraint for Cognitive Unmanned Aerial Vehicle Networks

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Abstract

In order to meet the rapid development of the unmanned aerial vehicle (UAV) communication needs, cooperative spectrum sensing (CSS) helps to identify unused spectrum for the primary users (PU). However, multi-UAV mode (MUM) requires the large communication resource in a cognitive UAV network, resulting in a severe decline of spectrum efficiency (SE) and energy efficiency (EE) and increase of energy consumption (EC). On this account, we extend the traditional 2D spectrum space to 3D spectrum space for the UAV network scenario and enable UAVs to proceed with spectrum sensing behaviors in this paper, and propose a novel multi-slot mode (MSM), in which the sensing slot is divided into multiple mini-slots within a UAV. Then, the CSS process is developed into a composite hypothesis testing problem. Furthermore, to improve SE and EE and reduce EC, we use the sequential detection to make a global decision about the PU channel status. Based on this, we also consider a truncation scenario of the sequential detection under the sensing delay constraint, and further derive a closed-form performance expression, in terms of the CSS performance and cooperative

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efficiency. At last, the simulation results verify that the performance and cooperative efficiency of MSM outperforms that of the traditional MUM in a low EC.

Keywords: Unmanned aerial vehicle; cooperative spectrum sensing; spectrum efficiency; energy efficiency; sensing delay constraint

1. Introduction

In the past few years, unmanned aerial vehicle (UAV) has been an important research object because of its autonomy and flexibility, which can be applied to various fields. At present, the application fields of UAV include military operations, geological survey, logistics and transportation, agricultural applications, film and television shooting, firefighting and disaster fighting, rescue patrol, and many other fields [1]. However, with the wide application of UAVs, the problem of scarce spectrum resources becomes increasingly serious. Federal Communications Commission (FCC) researches proved that the shortage of spectrum resources is due to the insufficient utilization of spectrum by primary users (PUs). In this regard, cognitive radio (CR) technology provides a new view for UAVs to optimistically access spectrum underutilized by the PUs [2], and the normal communication of the network of PUs will not be affected [3].

In such an integration paradigm of CR technology with UAVs, spectrum sensing is a key function to avoid the excessive interference with the PU's normal communication and detect the channel unused by the PU for UAVs to improve the spectrum utilization. Nevertheless, the spectrum sensing of a single node is vulnerable to noise uncertainty, multipath fading, shadowing and other factors of intrinsic nature of wireless communication [4-5]. In view of this, multiple small UAVs could work together to form a multi-UAV system, which improves the reliability and efficiency of cooperation. Such a multi-UAV mode (MUM) has two major advantages: low cost and good scalability. Therefore, CSS exploits spatial diversity via the observations of spatially located UAVs, aiming to improve the detection accuracy for the PU. In the process of CSS, multiple UAVs report their sensing results to the fusion center (FC) [6], and the FC is responsible for making a final decision about the PU's signal status by means of a specific fusion rule [7].

In fact, the integration between them is fairly unexplored in CSS [8-10], such as spectrum and energy consumption (EC). Regarding spectrum and EC, for UAVs to cover wide areas and long missions, spectrum efficiency (SE) and energy efficiency (EE) is necessary for cognitive UAV networks.

1.1 Related Work

Although CR and UAVs are established research fields, CSS among UAVs related to SE and EE has become a research hotspot as the researchers are expected to greatly influence and improve cooperation efficiency [11].

In [12], G. Verma et al. a new approach which with the help of the proposed decoder structure enables the CR system to execute the tasks of spectrum sensing and data transmission simultaneously, with aiming of improving the achievable throughput. In [13], C. Kan et al.

proposed an interference-aware spectrum sensing model to maximize throughput by using the optimal sensing time at different distances. On the basis of [14], the authors further improved the algorithm by optimizing the detection time and threshold. Undoubtedly, the optimization problem of the achievable throughput is carried out under the assumption that there is no sensing time constraint in [12-14], however this assumption may not be practical in a real spectrum sensing scenario. In [15], H. Hu et al. regarded several adjacent frames as a block, and proposed an improved CSS scheme to improve EE. Since the improvement of EE may lead to the decline of SE, the authors considered the trade-off between SE and EE in [16]. Similar to [15], to improve EE, C. Wang et al. proposed an energy-efficient CSS iterative power adaptation algorithm in [17]. Further, by comparing the hybrid spectrum sharing scheme and opportunistic spectrum access scheme under three hard fusion rules, the authors obtained the rule with the best EE in [18] and maximize EE while ensuring the service quality of users from the perspective of reducing energy loss in [19]. Unfortunately, these studies focus on SE and EE issues in 1D or 2D spectrum space. In fact, the increasing popularity of UAVs in both civil and military fields has been witnessed, which poses promising potentials to explore and exploit spectrum opportunity in 3D spectrum space. In [20], M. Khan et al. conducted a comprehensive investigation on flying ad hoc networks (FANETs), which provides a direction for exploring 3D spectrum space.

In view of this, Y. Zeng et al. obtained better EE by optimizing the velocity and acceleration during UAV flight in [21]. In [22], Y. Cai et al. optimized resource allocation strategy and UAV trajectory to improve EE. Considering the endurance capability of UAV, Y. Sun et al. used solar energy for UAVs and optimized the trajectory of UAV to achieve a balance between solar energy collection and energy saving in [23]. K. Li et al. proposed a new suboptimal algorithm in [24] to reduce scheduling complexity, save 50% energy and prolong network life. In the cognitive UAV network, the CSS between UAVs not only improves the detection performance, but also increases the energy loss. In [25], M. Hua et al. improved EE by optimizing the scheduling scheme, power allocation strategy and flight trajectory of sensor nodes. A virtual CSS was proposed by X. Liu in [26], which maximizes the throughput by optimizing the sensing radian. In [27], a new compressed signal algorithm was proposed by W. Xu to promote timely and effective communication in the UAV network. Y. Pan et al. proposed an algorithm using alternating optimization technology and dichotomy, and compared its performance with other algorithms to get a better algorithm to improve the efficiency of CR system in [28]. In [29], H. Hu et al. were committed to finding the best location of UAV and optimizing power allocation scheme to maximize throughput. Considering the particularly serious channel environment, an alternative iterative optimization algorithm was proposed in [30] to solve the optimization problem of SE. These research works pay attention to SE or EE optimization in MUM, but ignore significant communication overhead within a multi-UAV system resulting in a cooperative gain loss.

To reduce the communication overhead between the FC and UAVs in MUM, a fast and efficient CSS algorithm was proposed by H. Zhang in [31] to reduce the number of UAVs and ensure that the error rate is lower than a certain threshold. Based on quick detection theory, E. Hanafi et al. derived closed-form expressions to approximate the distribution of detection delay for a time-invariant cumulative sum detector in [32], while A. Badawy et al. derived closed-form expressions for the probability of false alarm and probability of detection for the quickest change detection-cumulative sum sequential test in [33]. J. Wu et al. proposed an energy-saving virtual CSS and sequential 0/1 fusion rule in [34], which reduces the average number of detections and further proposed an intra-frame CSS to undertake cooperation between multiple mini-slots and make an in-depth analysis on the benefit and cost of it in [35].

Although the above research has made contributions to optimize SE, EE or other performance metrics, there are still some limitations. In a multi-UAV system, some small drones connect to base stations or satellites, others communicate with cellular devices, the scarcity of spectrum resources is much severer. In front of this, the SE and EE issue in CSS remain unclear at present.

1.2 Our Contributions

The main contributions of this paper can be summarized as follows:

By leveraging the location flexibility of UAV spectrum sensors following circular flight trajectory, we define the 3D spectrum sensing behavior for the UAV sensing node and establish a cooperative working of multi-slot model (MSM) within a UAV as a composite hypothesis testing problem instead of the traditional MUM, based on which, we use the sequential detection as the fusion rule to make a global decision and improve cooperation efficiency.

On the basis of the sequential detection, we take the sensing delay constraint into consideration, with the aim of a balance between CSS performance and efficiency, conduct an in-depth investigation on various truncation scenarios, and further propose a soft truncation way to terminate the sequential process within the sensing delay constraint.

In the truncation-based sequential detection, we conduct the global detection performance, the false alarm probability, and the detection probability. By means of the performance expression, we also analyze SE, EC, and EE of the proposed multi-slot mode and the traditional MUM and thoracically derive closed-form expressions of SE, EC, and EE.

1.3 Organization

The rest of this paper is as follows. In Section 2, a network model and local spectrum sensing (LSS) model are established, the problem of interest is introduced. Section 3 introduces the sequential detection-based CSS and makes a brief presentation and analysis of MUM. A MSM within a single UAV is proposed to implement CSS and overcome the drawback of the traditional MUM in Section 4. Section 5 makes an in-depth analysis on the global detection performance, SE, EC and EE under the sensing delay constraint and derive closed-form performance expression. Our proposed MSM is verified by simulation results in Section 6. Finally, Section 7 concludes this paper.

2. System Model

In this section, we define a cognitive UAV network and model a CSS process, such as, CSS among multi-UAVs and CSS among multi-slots. Under this generalized CSS process, we also evaluate the LSS performance by means of air-to-ground channel.

2.1 Network Model

Considering a cognitive UAV network consisting of several UAVs and a PU, each UAV follows a circular flight trajectory in the space, where the flight height is h and flight radius is R, as shown in **Fig. 1(a)**, then the sensing distance for the UAV $d = \sqrt{h^2 + R^2}$. For the sake of simplicity of description, we take CSS among multiple UAVs as an example to elaborate the whole process.

In cognitive UAV network, each UAV individually detects the PU signal to make a local sensing decision by means of a specific signal detection technology. Assuming that the PU signal is a complex value phase shift keying (PSK) signal, and denoted by $s_i(z)$ at the ith UAV for the mth sampling, $u_i(z)$ is a circular symmetric complex Gaussian (CSCG) noise with variance σ_n^2, $s_i(z)$ and $u_i(z)$ are independent.

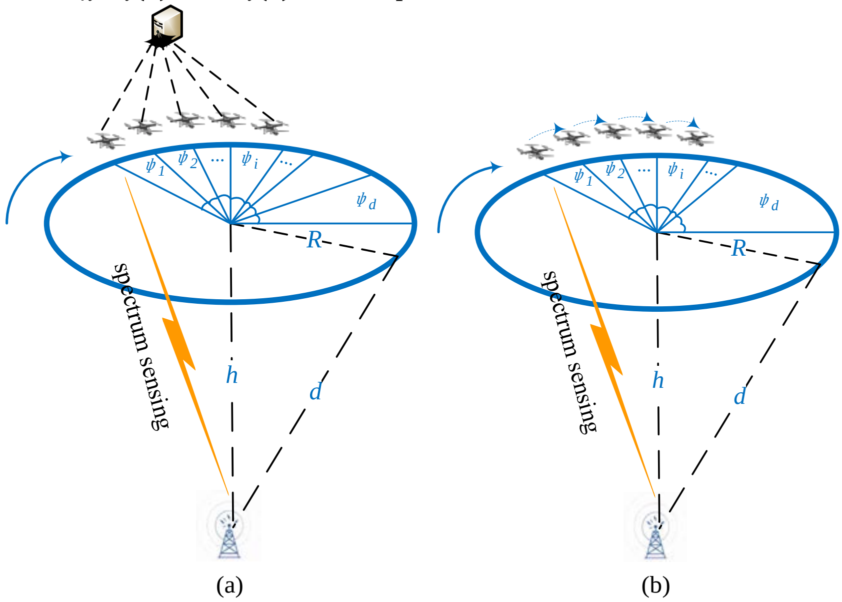

Fig. 1. CSS (a) multiple UAV model (b) multiple slots model.

Under the hypothesis H_0 where the PU is absent, the received signal by the UAV at the ith sensing slot is

$$y_i(z) = u_i(z) \tag{1}$$

Under the hypothesis H_1 where the PU is present, the received signal can be described as

$$y_i(z) = \sqrt{P_R(d_i)}s_i(z) + u_i(z) \tag{2}$$

where $P_R(d_i)$ is the attenuated received PU signal at the ith UAV with a distance d_i from the PU.

According to the PU signal model described above, each UAV should adopt signal detection technology to detect the phenomenon of the PU presence. Considering the simplicity and short sensing time, the energy detection is used as the signal detection technology. In the energy detection scheme, the measurement for energy detector E_i is calculated and compared with a detection threshold to make a binary local decision regarding the PU status, where

$$E_i = \frac{1}{Z}\sum_{z=1}^{Z}|y_i(z)|^2 \tag{3}$$

and Z is the number of signal samples at a sensing slot.

2.2 LSS Model

Following the network model and energy detection scheme, we further evaluate the LSS performance and investigate the impact of the air to ground channel on the LSS.

Depending on (3), for a large Z, E_i can be regarded as a Gaussian random variable under both the hypotheses H_0 and H_1 by means of central limit theorem (CLT), such as

$$E_i \sim \begin{cases} \mathcal{N}(\mu_0, \sigma_0^2), H_0 \\ \mathcal{N}(\mu_1, \sigma_1^2), H_1 \end{cases} \tag{4}$$

where $\mu_0 = \sigma_n^2$, $\sigma_0^2 = Z\sigma_n^2$, $\mu_1 = \mu_0(1+\gamma_i)$, $\sigma_1^2 = \sigma_0^2(1+2\gamma_i)$, and $\gamma_i = P_R(d_i)/\sigma_n^2$ is the signal-to-noise ratio (SNR) of the signal received in the ith slot.

According to the pre-determined λ, the LSS performance metrics including the false alarm probability $P_{f,i} = P(r_i = 1|H_0)$ and the detection probability $P_{d,i} = P(r_i = 1|H_1)$, can be respectively expressed as [36]

$$P_{f,i} = \mathcal{Q}\left((\lambda/\sigma_n^2 - 1)\sqrt{\tau_{s,i} f}\right) \tag{5}$$

$$P_{d,i} = \mathcal{Q}\left((\lambda/\sigma_n^2 - \gamma_i - 1)\sqrt{\lambda\tau_{s,i} f/(1+2\gamma_i)}\right) \tag{6}$$

where r_i is the local decision of at the ith UAV, $\tau_{s,i}$ is the sensing time at the ith sensing slot, f is the carrier frequency, $\mathcal{Q}(\cdot)$ is the complementary distribution function of the standard Gaussian.

Since the probability of receiving line of sight (LOS) and strong non-line of sight (NLOS) components are significantly higher than fading in cognitive UAV network [37], the impact of small-scale fading can be neglected. Therefore, the received PU signal power $P_R(d_i)$ can be described as [38]

$$P_R(d_i) = P_t - \bar{L}_i \tag{7}$$

$$\bar{L}_i = P_{los}(L_i + \xi_{los}) + P_{nlos}(L_i + \xi_{nlos}) \tag{8}$$

where P_{los} and P_{nlos} are the probabilities of the LOS link and NLOS link, $P_{los} = 1/\{1 + \alpha\exp[-\beta(180\pi/\vartheta - \alpha)]\}$, $\vartheta = arctan(h/R)$, $P_{nlos} = 1 - P_{los}$, α, β are the parameters, which decided by environment, $L_i = 20log(4\pi f d_i/c)$ is the average path loss, c is the speed of light, ξ_{los} and ξ_{nlos} are the average additional loss to the free space propagation loss, which depend on the environment.

3. Cooperative Working Model

In this section, we embed the sequential detection into the CSS process to improve the cooperative efficiency. On the basis of this, we further make an in-depth analysis on the traditional MUM, especially in a defective aspect. Sequentially, we propose a new MSM to implement the cooperative working among multiple sensing slots, aiming at the improvement of SE and EE.

3.1 Sequential Detection-based CSS

In the process of CSS, the FC employs a specific fusion rule technique to make a global decision about the PU status [39]. In fact, there are various fusion rules that can be used in support of the global decision-making, i.e., decision fusion, Bayesian detection, Neyman-Pearson test etc., but there also exists the fixed-sample-size detection problems where the global decision is made after receiving the entire set of local decisions. Undoubtedly, such a kind of fixed-sample-size fusion rule cannot satisfy the requirement of SE and EE for some scenarios in cognitive UAV networks. Motivated by this, the sequential detector will make a final decision at the FC and terminate the sequential process as soon as the CSS system are satisfied with the decision condition or continue to take additional local decisions, because the local decisions arrive sequentially at the detector. In the sequential decision process, after each local decision, the FC computes the likelihood ratio Λ_m, which is expressed by (9) where m is the required number of the local decisions and compares it with two thresholds, such as, the lower threshold δ_0 and the upper threshold δ_1. Either it decides on one of the hypotheses H_0 and H_1 or it decides to take another local decision. Obviously, the main advantage of the sequential detection is that it requires, on an average, fewer local decisions to achieve the same detection performance as a fixed-sample-size fusion rule [40].

In details, after the FC receives the first local decision, Λ_1 is calculated and compared with δ_0 and δ_1 where $\delta_0 = (1-\bar{P}_d)/\left(1-\bar{P}_f\right)$ and $\delta_0 = \bar{P}_d/\bar{P}_f$, $\bar{P}_d$ and $\bar{P}_f$ are the tolerated detection probability and the tolerated false alarm probability, respectively, the FC announces that the PU is absent if $\Lambda_1 \leq \delta_0$; the FC declares that the PU is present $\Lambda_1 \geq \delta_1$; otherwise, the FC needs to take the second local decision if $\delta_0 < \Lambda_1 < \delta_1$, calculates $\Lambda_2 = \Lambda_1 \cdot \frac{P(r_2|H_1)}{P(r_2|H_0)}$ and still compares it with δ_0 and δ_1, and so on. That is to say, the following local decisions are not required once the FC has made a global decision.

$$\Lambda_m = \prod_{i=1}^{m} \frac{P(r_i|H_1)}{P(r_i|H_0)} = \prod_{i=1}^{m} \left(\frac{P(r_i=1|H_1)}{P(r_i=1|H_0)}\right)^{r_i} \left(\frac{P(r_i=0|H_1)}{P(r_i=0|H_0)}\right)^{1-r_i}$$
$$= \prod_{i=1}^{m} \left(\frac{P_{d,i}}{P_{f,i}}\right)^{r_i} \left(\frac{1-P_{d,i}}{1-P_{f,i}}\right)^{1-r_i} \quad (9)$$

3.2 MUM

Following CSS among multiple UAVs model and the sequential detection, a brief presentation of MUM is provided.

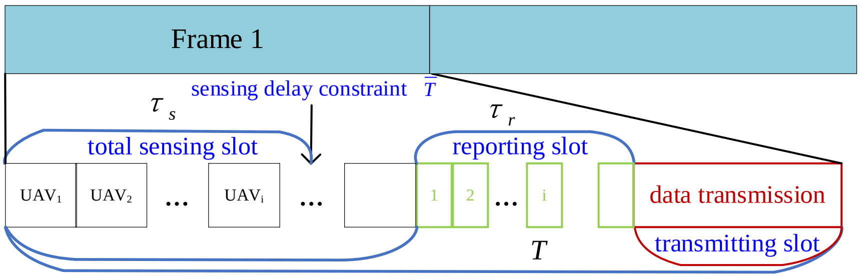

Fig. 2. MUM illustration.

As shown in **Figs. 1(a)** and **2**, the ith UAV with the help of the energy detection scheme performs the LSS in the same flight parameters (the flight radius, flight height and fight velocity) at the ith sensing slot, and flight radian is φ_i within the sensing time $\tau_{s,i}$. After all M UAVs independently implement the LSS and make a local decision (the total sensing time $\tau_s = \sum_{i=1}^{M} \tau_{s,i}$), each UAV sequentially submits own binary decision 0 or 1 about the PU status to the FC via the reporting channel at the reporting slot, where 0 represents the absence and 1 represents the presence. The reporting time is $\tau_{r,i}$ for the ith UAV. After m $(1 \leq m \leq M)$ local decisions arrive at the FC (then the total reporting time $\tau_r = \sum_{i=1}^{m} \tau_{r,i}$, correspondingly, the flight radian is φ_r within τ_r), the FC adopts the sequential detection to make a global decision about the PU status. The FC will broadcast the message that the channel is utilized by the PU to all UAVs if the global decision is 1. At this time, UAVs are forbidden to access the channel and will continue spectrum sensing at the next sensing frame l. When the FC makes a global decision 0, then UAVs will be broadcasted to access the channel for data transmission by a specific spectrum resources allocation algorithm at the transmitting slot, where the transmitting time is denoted by τ_d, the corresponding flight radian is φ_d.

The CSS process illustrated above is the working mode of MUM. Let T represent a fixed frame duration for a periodic spectrum sensing in cognitive UAV network, then $T = \sum_{i=1}^{M} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i} + \tau_d$. Apparently, compared with those fixed-sample-size fusion rules wherein $\tau_d = T - \left(\sum_{i=1}^{M} \tau_{s,i} + \sum_{i=1}^{M} \tau_{r,i}\right)$, the sequential detection is more efficiency because the reporting time is shorter. However, UAVs still need to directly connect to the FC during the CSS process, on the one hand, it will produce significant communication overhead regardless of whether UAVs submit local decision to the FC or the FC broadcasts the channel status to UAVs at the reporting channel; on the other hand, the reporting channel may be affected by the nature of wireless propagations while the FC also may suffer from a hardware failure. In terms of SE and EE, MUM still has a lot of room for improvement in cognitive UAV networks.

4. MSM

In view of the disadvantages of MUM, a simple but high efficiency cooperation working mode for CSS is proposed in this section. For this aim, we first take the sensing delay constraint into account and further thoroughly discuss two cases of CSS under sensing delay constraint. On the basis of the sensing delay constraint, a simple soft truncation is designed when the sequential detection is terminated.

4.1 Sensing Delay Constraint

Before proceeding with the description of MSM, we take the sensing delay constraint into consideration and give MUM as an example to present two cases in the following discussions.

Case 1: when $\overline{T} \geq \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, the spectrum sensing process is not limited by the sensing delay constraint, the sequential detection can be normally implemented.

Case 2: when $\overline{T} < \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, the FC cannot reach a global decision within $\overline{T}$, then the sequential detection will be terminated. To be specific, the LSS will be interrupted at each UAV if $\overline{T} < \sum_{i=1}^{m} \tau_{s,i}$. Otherwise, when $\sum_{i=1}^{m} \tau_{s,i} \leq \overline{T} < \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, all M UAVs have finished the LSS, but the local decisions have not had time to be fully submitted to the FC.

Since the time of the sequential detection to reach a decision at the FC is random, a quick CSS is indispensable and therefore devising a high-efficient cooperation working mode for the PU signal detection of UAVs becomes essential. It is known that the cooperative paradigm has been proposed to improve detection accuracy by exploiting UAVs' spatial diversity in cognitive UAV networks. In the practical implement of UAVs, since the connectivity cannot be guaranteed due to the surrounding sensing environments, it is a difficult task for UAVs to simultaneously participate in CSS. In this regard, we consider another cooperation working mode to achieve cooperative gain from various sensing slots at various spatial location of a UAV.

From **Fig. 1(b)**, the sensing time is invariant at the sensing slot of a UAV. In details, a UAV takes the sensing time $\tau_{s,1}$ to detect the PU at the first sensing slot, and it takes the sensing time $\tau_{s,2}$ to continue to detect at the second sensing slot, and so on. Since the UAV's location varies as time progresses, the same UAV makes multiple local decisions by means of the energy detection scheme at different location/time at the same UAV, then which conducts an approximate CSS, that is MSM. Though the MSM is similar to MUM at the sensing slot (the difference is that the local decision from each UAV's sensing slot becomes the decision from the same UAV's different sensing slot), the FC and the reporting slot is no longer required. This is because when the CSS process is implemented at a UAV, the UAV totally completes the fusion of local decisions by itself. After the UAV makes a global decision according to the local decision from various sensing slots, then it can decide whether to access the PU channel and has the limitations of spectrum resources allocation algorithms. It is apparent that the CSS is more flexible and easier to apply into the multiple PUs scenario in MSM. This can be attributed to the fact that MSM can perform the sequential detection while performing LSS. More importantly, only $\overline{T} \geq \sum_{i=1}^{m} \tau_{s,i}$ is satisfied, the sequential detection can be completed normally, meanwhile the data transmission time $\tau_d = T - \sum_{i=1}^{m} \tau_{s,i}$ has been greatly extended, as illustrated in **Fig. 3**.

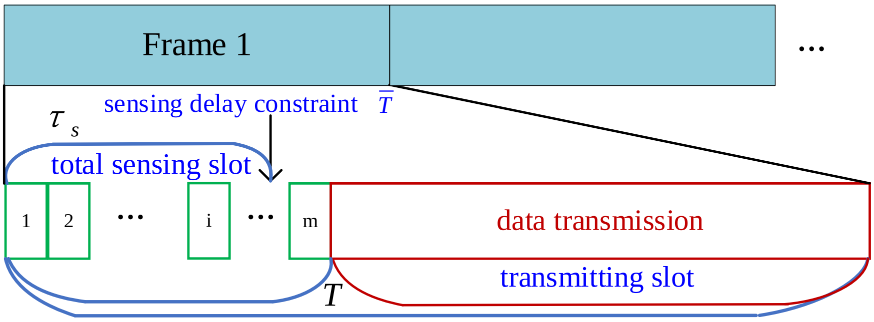

Fig. 3. MSM illustration.

4.2 Soft Truncation

Though the sequential detection can always be terminated, the number of local decisions required by the termination condition may be large [41]. In other words, m may be approach to M in $\tau_s = \sum_{i=1}^{m} \tau_{s,i}$, $\overline{T} \geq \sum_{i=1}^{m} \tau_{s,i}$ cannot be always satisfied. Hence, the truncation of the sequential detection should be carefully considered in a practical implementation after the total sensing time exceeds the sensing delay constraint.

At the truncation stage of the sequential detection, the sequential detector is forced to make a global decision in favor of H_0 or H_1 when $\overline{T} < \sum_{i=1}^{m} \tau_{s,i}$. Assuming that $\overline{T}$ is an integer multiple of $\tau_{s,i}$ and $\overline{T} = \sum_{i=1}^{\overline{m}} \tau_{s,i}$ where $1 \leq \overline{m} \leq m$, then we have the following inequity

$$\delta_0 < \Lambda_{\overline{m}} = \prod_{i=1}^{\overline{m}} \frac{P(r_i|H_1)}{P(r_i|H_0)} < \delta_1 \tag{10}$$

Then, we define a pre-setting threshold for the truncation stage as $\bar{\delta} = (\delta_0 + \delta_1)/2$, the sequential detector accepts H_1 if $\Lambda_{\overline{m}} \geq \bar{\delta}$, otherwise it accepts H_0.

5. Performance Analysis Of MSM

Relying on the proposed MSM, we derive the closed-form expression of the CSS performance under the sensing delay constraint, in terms of the global false alarm probability and detection probability. Furthermore, we analyze SE, EC and EE of both MUM and MSM, and theoretically demonstrate the superiority of our proposal.

5.1 CSS Performance

For simplicity of the CSS performance evaluation, we assume that the LSS performance, the sensing time are same at each sensing slot, i.e., $P_{d,i} = P_d$, $P_{f,i} = P_f$, $\tau_{s,i} = \bar{\tau}_s$, and $\tau_{r,i} = \bar{\tau}_r$. Then, we have the following result from (9)

$$log\Lambda_m = \sum_{i=1}^{m}\left[r_i log\left(\frac{P_{d,i}}{P_{f,i}}\right) + (1-r_i)log\left(\frac{1-P_{d,i}}{1-P_{f,i}}\right)\right] \tag{11}$$

According to CLT, $log\Lambda_m$ is also regarded as a Gaussian random variable, which is expressed by

$$log\Lambda_m \sim \begin{cases} M\left(m\varphi_0, m\varphi P_f\left(1-P_f\right)\right), H_0 \\ M\left(m\varphi_1, m\varphi P_d(1-P_d)\right), H_1 \end{cases} \tag{12}$$

where $\varphi_0 = P_f log\left(\frac{P_d}{P_f}\right) + \left(1-P_f\right)log\left(\frac{1-P_d}{1-P_f}\right)$, $\varphi_1 = P_d log\left(\frac{P_d}{P_f}\right) + (1-P_d)log\left(\frac{1-P_d}{1-P_f}\right)$ and $\varphi = log\left(\frac{(1-P_d)P_d}{(1-P_f)P_f}\right)$.

When $\bar{T} \geq \sum_{i=1}^{m}\tau_{r,i}$, the sequential detection-based CSS in MSM is normally completed, then we have the global false alarm probability and the global detection probability are respectively obtained by

$$Q_{f,1} = P(log\Lambda_m > log\delta_1|H_0) = Q\left(\xi_{0,0}\right) \tag{13}$$

$$Q_{d,1} = P(log\Lambda_m > log\delta_1|H_1) = Q\left(\xi_{1,0}\right) \tag{14}$$

where $\xi_{0,0} = (log\delta_1 -)/\sqrt{\bar{T}\beta_0}$ and $\xi_{1,0} = (log\delta_1 - \varphi_1\bar{T}/\bar{\tau}_s)/\sqrt{\bar{T}\beta_1}$, $\beta_0 = \varphi P_f\left(1-P_f\right)/\bar{\tau}_s$ and $\beta_1 = \varphi P_d(1-P_d)/\bar{\tau}_s$.

When $\bar{T} < \sum_{i=1}^{m}\tau_{r,i}$, the sequential detection process is truncated, according to the soft truncation, we have

$$Q_{f,2} = P\left(log\Lambda_m > log\bar{\delta}\middle|H_0\right) = Q\left(\xi_{0,0}\right) \tag{15}$$

$$Q_{d,2} = P\left(log\Lambda_m > log\bar{\delta}\middle|H_1\right) = Q\left(\xi_{1,0}\right) \tag{16}$$

where $\xi_{0,0} = \left(log\bar{\delta} - \varphi_0\bar{T}/\bar{\tau}_s\right)/\sqrt{\bar{T}\beta_0}$ and $\xi_{1,0} = \left(log\bar{\delta} - \varphi_1\bar{T}/\bar{\tau}_s\right)/\sqrt{\bar{T}\beta_1}$.

It is worth noting that the difference of MUM and MSM is the cooperation way, the detection performance is the same if the reporting slot and the FC is ignored. In fact, unless $\bar{T} \geq \sum_{i=1}^{m}\tau_{s,i} + \sum_{i=1}^{m}\tau_{r,i}$, MUM cannot complete the sequential detection of CSS.

5.2 SE And EE

Following the CSS performance, the next thing comes into consideration is how to evaluate SE and EE. Similar to the CSS performance evaluation, SE and EE should be also categorized into various scenarios under the sensing delay constraint.

5.2.1 SE Evaluation

Now, we start with investigation on the throughput of two scenarios in cognitive UAV network. Assuming that SNR for the cognitive UAV network link is denoted by $SNR_u = P_u/\sigma_n^2$ [32], where P_u is the transmitting power of the UAV. When the PU is accurately determined as the absence, the throughput can be given by

$$C_0 = log_2(1 + SNR_u) \tag{17}$$

When the PU is mistakenly determined as the absence, the throughput in this scenario can be given by

$$C_1 = log_2\left(1 + \frac{P_u}{P_R + \sigma_n^2}\right) = log_2\left(1 + \frac{SNR_u}{SNR_p + 1}\right) \tag{18}$$

where $SNR_p = P_R(d)/\sigma_n^2$, $P_R(d) = P_R(d_i)$.

Through above analyses, assuming that each reporting time for each local decision is $\bar{\tau}_r$ in MUM, i.e., $\tau_{r,i} = \bar{\tau}_r$, $P(H_0)$ and $P(H_1)$ are respectively the probability of hypotheses H_0 and H_1, then we have following conclusions.

(a) If $\sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i} \le \bar{T}$, then SE of MSM and MUM can be respectively expressed as (19) and (20);

$$\eta_{SE,MSM} = (T - m\bar{\tau}_s)\big(P(H_0)(1 - Q_{f,1})C_0 + P(H_1)(1 - Q_{d,1})C_1\big)/T \tag{19}$$

$$\eta_{SE,MUM} = \big(T - m(\bar{\tau}_s + \bar{\tau}_r)\big)\big(P(H_0)(1 - Q_{f,1})C_0 + P(H_1)(1 - Q_{d,1})C_1\big)/T \tag{20}$$

(b) If $\bar{T} < \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, then SE of MUM is 0 and further

if $\sum_{i=1}^{M} \tau_{s,i} \le \bar{T} < \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, then SE of MSM is still (19);

if $\bar{T} < \sum_{i=1}^{m} \tau_{s,i}$, then SE of MSM is given by (21).

$$\eta_{SE,MSM} = (T - \bar{T})\big(P(H_0)(1 - Q_{f,2})C_0 + P(H_1)(1 - Q_{d,2})C_1\big)/T \tag{21}$$

5.2.2 EE Evaluation

To evaluate EE, we start with conducting EC in the process of CSS. To this end, we consider the utility of the cognitive UAV network. Assuming that at each sensing slot, P_s is defined as the sensing power consumed, P_c is the circuit power consumed by electronic devices, P_r is the power required for reporting at the reporting slot. Then, we also have following conclusions.

(a) If $\sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i} \le \bar{T}$, EC of MSM and MUM can be respectively defined as

$$\eta_{EC,MSM} = m\bar{\tau}_s(P_s + P_c) + (T - m\bar{\tau}_s)\Big(P(H_0)(1 - Q_{f,1}) + P(H_1)(1 - Q_{d,1})\Big)(P_u + P_c) \tag{22}$$

$$\eta_{EC,MUM} = m\bar{\tau}_s(P_s + P_r) + m(\bar{\tau}_s + \bar{\tau}_r)P_c + \big(T - m(\bar{\tau}_s + \bar{\tau}_r)\big)\big(P(H_0)(1 - Q_{f,1}) + P(H_1)(1 - Q_{d,1})C_1\big)(P_u + P_c) \tag{23}$$

(b) If $\bar{T} < \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, and further

if $\sum_{i=1}^{m} \tau_{s,i} \le \bar{T} < \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, EC of MSM can be still expressed (22) while that of MUM is expressed as

$$\eta_{EC,MUM} = m\bar{\tau}_s P_s + (\bar{T} - m\bar{\tau}_s)P_r + \bar{T}P_c \tag{24}$$

if $\bar{T} < \sum_{i=1}^{m} \tau_{s,i}$, EC of MSM is expressed as

$$\eta_{EC,MSM} = \bar{T}(P_s + P_c) + (T - \bar{T})\Big(P(H_0)(1 - Q_{f,2}) + P(H_1)(1 - Q_{d,2})\Big)(P_u + P_c) \tag{25}$$

and EC of MUM is given by

$$\eta_{EC,MUM} = \bar{T}(P_s + P_c) \tag{26}$$

Following SE and EC of CSS, EE can be described as

$$\eta_{EE} = \eta_{SE} * T/\eta_{EC} \tag{27}$$

In summary, it is easy to conduct out closed-form expressions of EE and verify that SE and EE of MSM are better than that of MUM.

6.Simulation Results

In this section, we give numerical simulation to verify the correctness and effectiveness of the proposed MSM under the sensing delay constraint, in terms of the detection performance and cooperative efficiency. Unless otherwise specified, the values of important simulation parameters are shown in **Table 1**.

Table 1. Simulation parameters

Symbol	Parameter	Value
P_u	Transmitting power of the PU	3 W
T	Each frame duration	100 ms
$\bar{\tau}_s$	Each sensing duration	1 ms
$\bar{\tau}_r$	Each reporting duration	1 ms
λ	Detection threshold	1.0115
$P(H_0)$	Probability of hypotheses about the PU status	0.8
$P(H_1)$		0.2
$\bar{P}_d$	Tolerated detection probability	0.9
$\bar{P}_f$	Tolerated false alarm probability	0.1
h	Flight height	500 m
c	Light speed	$3*10^8$ m/s
β	Environment parameters	0.28
α		9.6
f	Carrier frequency	2 MHz
σ_n	Noise standard variance	1
P_c	Circuit power	0.08 W
P_r	Reporting power	0.02 W
P_s	Sensing power	0.04 W
SNR_p	SNR of the PU	$10^{-1.5}$ dB
SNR_u	SNR of the UAV	10 dB
ξ_{los}	The average additional loss	1
ξ_{nlos}		20

6.1 Detection Performance

Since MUM cannot carry out effective CSS unless multiple UAVs can fully complete the LSS and report their local decisions to the FC within the sensing delay constraint, the signal detection for the PU cannot be implemented if $\overline{T} < \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$. But when $\overline{T} \geq \sum_{i=1}^{m} \tau_{s,i} + \sum_{i=1}^{m} \tau_{r,i}$, MUM has the same detection performance as MSM, because there is no missing sensing information in MUM.

In contrast, the CSS completion under MSM is not affected by the sensing delay constraint. As shown in **Figs. 4** and **5**, the sensing delay constraint varies from 1ms to 50ms at an interval of 1ms, we can see that the detection probability fluctuates and increases as the sensing delay constraint gradually relaxes. This is due to the fact that, MSM has more time to process local decisions through sequential detection, so it has better detection probability, while within the sensing delay constraint, i.e., $\overline{T} < \sum_{i=1}^{m} \tau_{s,i}$, the truncation of sequential detection directly results in the volatility of the detection probability. As the sensing delay constraint further increases, the detection probability also increases and tends to be stable. Otherwise, it also can be seen that for a fixed sensing delay constraint, the larger the flight radius, the worse the detection probability. It is obvious that a larger flight radius increases the sensing distance, thereby degrading the detection probability.

Compared to the detection probability, though the false alarm probability also fluctuates and increases as the sensing delay constraint increases, its increase is not large, especially in various flight radius. There are several reasons for this: (a) the local false alarm probability is not affected by SNR; (b) there is a classical tradeoff between the false alarm probability and detection probability; (c) the soft truncation way is more inclined to obtain spectrum resources for cognitive UAV networks than to suppress interference to the PU.

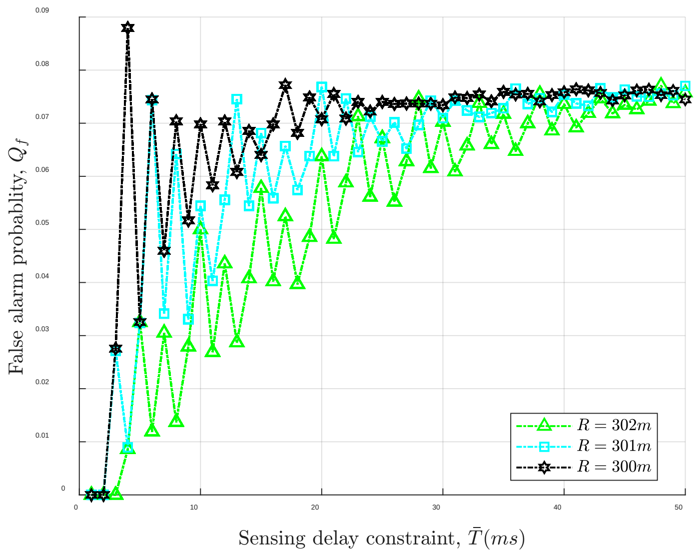

Fig. 4. The false alarm probability under sensing delay constraint.

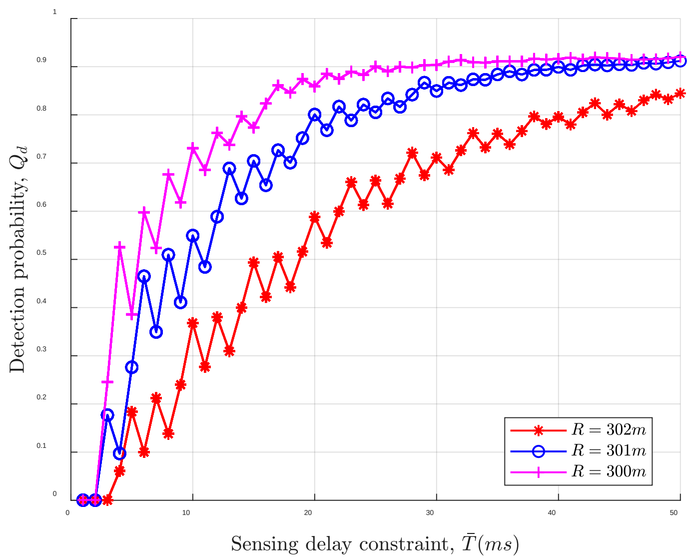

Fig. 5. The detection probability under sensing delay constraint.

6.2 Cooperative Efficiency

Next, we further discuss the efficiency of the cooperative working mode, in terms of SE, EC and EE.

In **Fig. 6**, SE comparison of MSM and MUM under the sensing delay constraint are displayed at various flight radius. SE of MUM is 0 at the beginning, this is not a surprise, and is in fact a direct consequence of the incomplete CSS within the sensing delay constraint. Once the CSS process is finished within a loose sensing delay constraint, MUM can achieve spectrum resources for the UAV. Since $C_0 > C_1$, the first term in the right-hand side of (20) dominates SE, then SE gradually decreases as the false alarm probability increases when the sensing delay constraint varies from 5ms to 22ms, but the smaller the flight radius is, the slower SE will decrease. When $\bar{T} = 22ms$, the false alarm probability is almost the same at various flight radius, while the detection probability also stabilizes when $R = 300m$ and the detection probability still increases under other flight radius. As a result, after $\bar{T}$ exceeds 22ms, the higher SE, the smaller the flight radius.

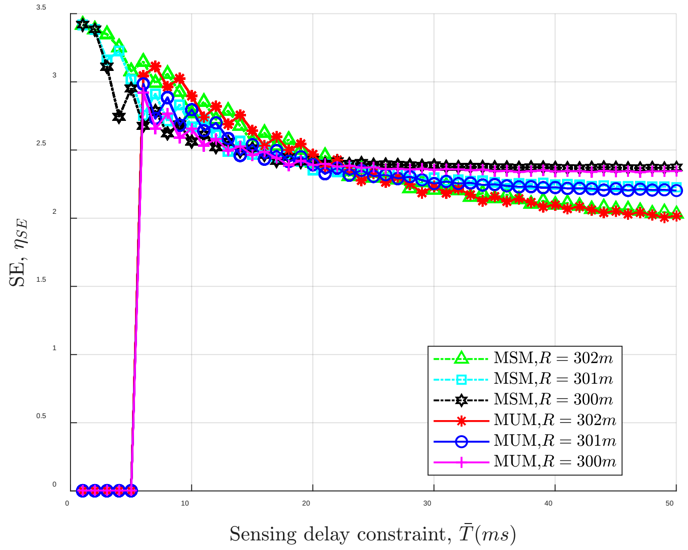

Fig. 6. SE under sensing delay constraint.

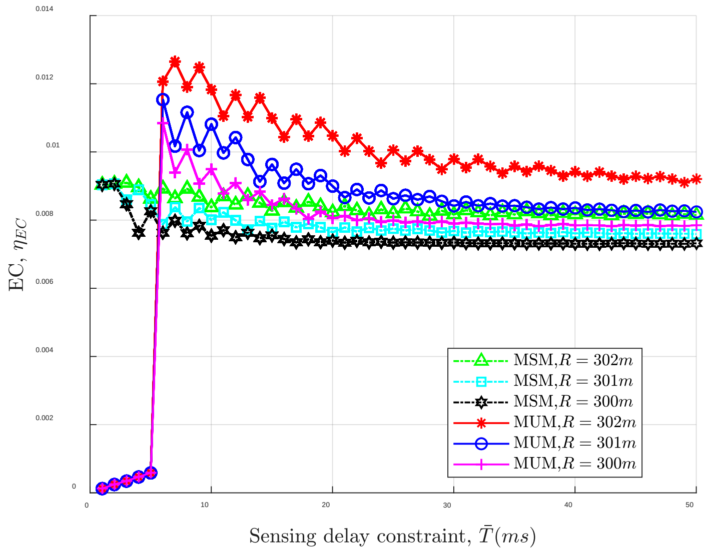

Fig. 7. EC under sensing delay constraint.

In fact, the similar conclusion can be draw in SE of MSM when $\bar{T} > 5ms$. Unlikely, MSM has a remarkable SE when $\bar{T} \leq 5ms$, because the soft truncation makes MSM completely implement CSS. Moreover, even the sensing delay constraint is relaxed, SE of MSM is still higher than that of MUM. This is reasonable, because the local decisions are always submitted to the FC via the reporting channel after the LSS is completed in MUM while the local decisions in MSM can be directly fused in the sequential detection at the UAV, and there is no such restriction.

From **Fig. 7**, EC of MSM and MUM is illustrated. It can be clearly observed that the EC of MSM is higher than that of MUM at the beginning. The reason for this phenomenon is that MSM can perform the LSS while fusing local decision and MUM only performs the LSS first within a strict sensing delay constraint. However, if the sensing delay constraint enables CSS to be completed under MUM, then EC sharply increases because the submission of local decisions also needs energy consumption. The sensing delay constraint further increases, which results in the great detection performance but shorten the data transmission time. Consequently, the total EC gradually decreases.

Different from EC of MUM, EC of MSM is relatively stable there is no a submission stage of local decisions. In addition, regardless of cooperative working mode, the larger the flight radius, the higher EC. The reason is that a larger flight radius leads to a worse local detection performance, thereby consuming more time and energy to perform the local sensing and decision.

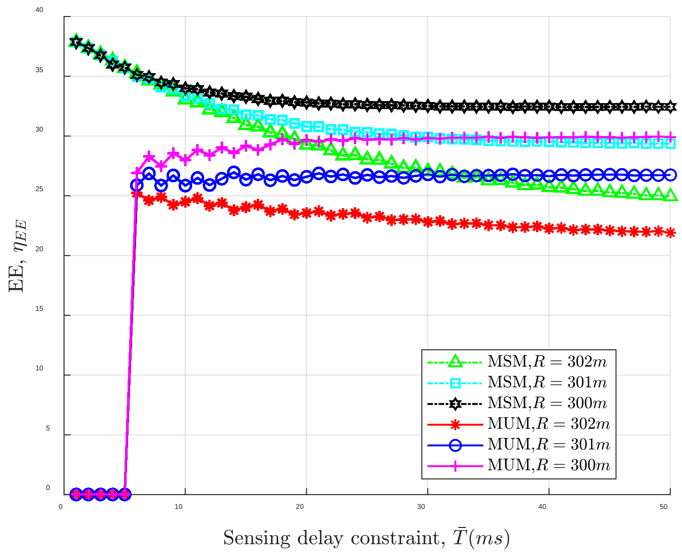

Fig. 8. EE under sensing delay constraint.

The EE comparison of two cooperative working modes is presented in **Fig. 8**. Combining **Figs. 6** and **7**, EE related to the sensing delay constraint and the flight radius is easily analyzed. For example, at the beginning, EE of MUM is 0 (because CSS is uncompleted), and then gradually increases, decreases, or basically keeps unchanged, which depends on the flight radius (because there is a tradeoff between the LSS time and the data transmission time in the fixed frame duration of MUM). In contrast to MUM, EE of MSM decreases and gradually stabilizes as the sensing delay constraint increases. This can be attributed to the trend of EE and EC following the sensing delay constraint.

6.3 Overprotection For PU

By a series of simulation results, it can be clearly observed that our proposed MSM outperforms MUM, in terms of the detection performance and cooperative efficiency. Nevertheless, it is worth noting that under the sensing delay constraint, the soft truncation of

MSM makes the CSS performance unstable, i.e., the fluctuant detection probability, thereby causing excessive interference to the primary network. To restrict the harmful interference to the PU, a hard truncation way, which integrates overprotection mechanism into sequential detection is taken into consideration in MSM. In details, when the sequential detection cannot be made a global decision about the PU status within the sensing delay constraint, the sequential detector will automatically treat the PU as presence.

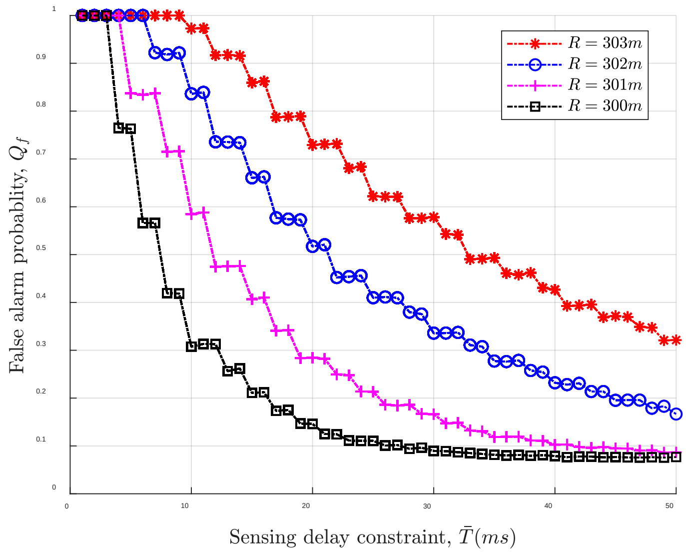

Fig. 9. The false alarm probability under hard truncation.

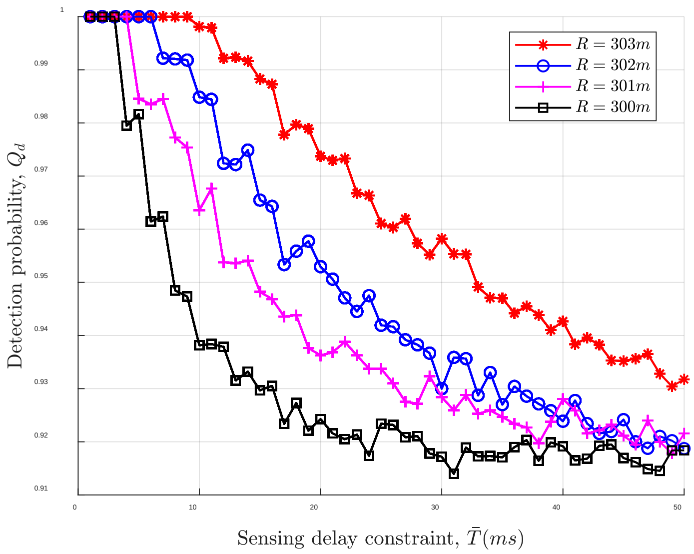

Fig. 10. The detection probability under hard truncation.

Under this hard truncation, the detection performance and cooperative efficiency are analyzed by simulations. As can be seen from **Figs. 9** and **10**, though the false alarm probability is high at the beginning, the increasing sensing delay constraint makes it quickly decrease. Furthermore, the detection probability is also high, and basically keeps a remarkable level. Though the hard truncation wastes a certain amount of spectrum resources (an appropriate flight radius can make up for this shortcoming), it also suppresses interference to the PU. Since the false alarm probability dominates SE, and the detection probability only decreases from 1 to 0.9, then the trend of SE with the sensing delay constraint is consistent with the false alarm probability, that is, $1 - Q_{f,1}$ or $1 - Q_{f,2}$. According to (22) and (25), it is known that the trend of EC is also similar to the false alarm probability. Following SE and EC, EE is 0 at the beginning, the strict sensing delay constraint leads to a hard truncation, hence the UAV cannot access the channel that may be not utilized by the PU. A relax sensing delay constraint gradually reduces the occurrence of the hard truncation, especially under a small flight radius.

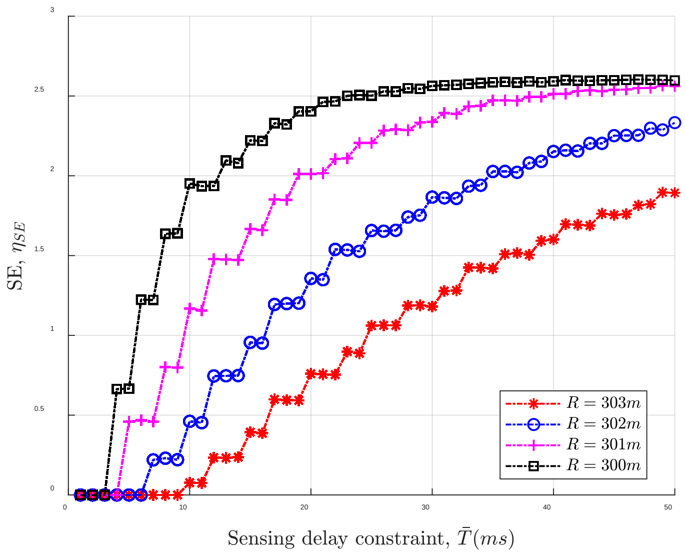

Fig. 11. SE under hard truncation.

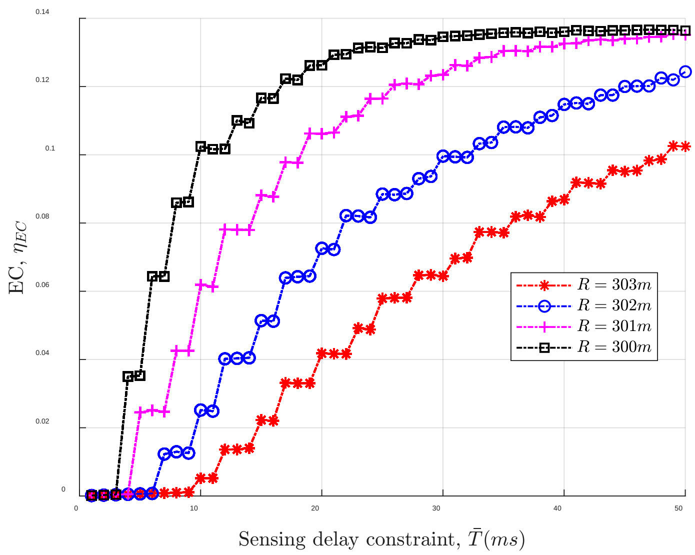

Fig. 12. EC under hard truncation.

Compared to EE of the soft truncation in MSM, it is seen from **Figs. 11** to **13** that EE of the hard truncation is worse than that of the soft truncation, this is obviously a direct consequence of the protection of the PU at the expense of wasting spectrum resources.

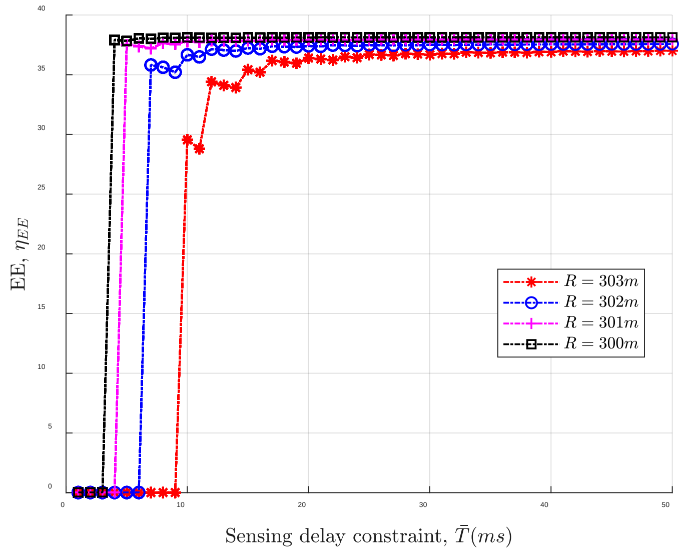

Fig. 13. EE under hard truncation.

7. Conclusions and Future Work

In this paper, we make an in-depth investigation on the CSS performance and cooperative efficiency under the sensing delay constraint in cognitive UAV networks. To this end, we define a 3D spectrum sensing behavior for the UAV sensing node and model a cooperative working model of MSM as a composite hypothesis testing problem. Based on this a generalized spectrum sensing model of the UAV, the sequential detection is adopted in the fusion rule to make a global decision. Furthermore, we further propose a soft truncation way in MSM to terminate the sequential process within the sensing delay constraint. In the soft truncation-based sequential detection, we analyze the CSS performance and cooperative efficiency and derived the closed-form expressions of them. Finally, a series of simulation results verify that in contrast to MUM, the better performance and cooperative efficiency can be provided in MUM with a low EC.

Although considerable efforts have been made in CSS, the optimization problem of SE, EE, and EC are still a major challenge in practical applications due to many factors such as various channel model and flight trajectory. This is an interesting question worth exploring in the future work.

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