IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received November 28, 2018, accepted December 6, 2018, date of publication January 1, 2019, date of current version January 23, 2019.

Digital Object Identifier 10.1109/ACCESS.2018.2890100

Resource Allocation Method of Cognitive Satellite Terrestrial Networks Under Non-Ideal Spectrum Sensing

WEILONG WANG[1], **SHANGHONG ZHAO**[1], **YONGXING ZHENG**[1,2], **AND YONGJUN LI**[1]

[1]Information and Navigation College, Air Force Engineering University, Xi'an 710038, China
[2]National Key Laboratory of Science and Technology on Space Microwave, Xi'an 710077, China

Corresponding author: Weilong Wang (wwlwangyi@126.com)

This work was supported by the National Natural Science Foundation of China under Grant 61231012, Grant 61701400, and Grant 61701522.

ABSTRACT Recently, the cognitive satellite communication has attracted more attention because of the high spectrum efficiency in the satellite bands. This paper investigates a distributed joint resource allocation algorithm based on the convex optimization theory in the cognitive satellite terrestrial networks under non-ideal spectrum sensing. In the cognitive satellite terrestrial network scenario, satellite users act as secondary users (SUs) who have the ability to transmit over multiple and simultaneous radio access technologies (RATs). Considering primary user activity modeling, the goal of the proposed algorithm is to minimize the end-to-end delay of the SUs in an actual propagation channel scenario. The bandwidth of different RATs and the power of different SUs are jointly allocated, and then, the data being transported by each SU are sent based on the allocated bandwidth and power. The numerical results validate the performance enhancement of the proposed algorithm and show the impact of channel condition parameters on the SUs' delays under non-ideal spectrum sensing. The SUs transmission delays reduce by 81.31% after the resource allocation when the mean of primary user activity matrix is 0.9.

INDEX TERMS Cognitive satellite communication, resources allocation, primary user activity matrix, convex optimization.

I. INTRODUCTION

Compared with terrestrial traditional networks, satellite networks have outstanding advantages in communication capacity, coverage area and transmission quality. Satellite communication plays a significant role in future wireless communication, especially in remote and sparsely populated locations [1]. However, the available satellite spectrum is becoming scarce because of the rising demands of satellite broadcasting and multimedia services. Satellite bands are under the increasing pressure, especially in L and C bands for the adoption of terrestrial services such as LTE and WiMax services. It becomes an important challenge to explore new techniques for increasing spectrum efficiency in satellite communication [2]. To settle the spectrum scarcity, cognitive radio (CR) communication can be considered as a promising technique to rise the overall spectrum efficiency in satellite networks scenario. CR techniques allow two satellite networks or satellite terrestrial hybrid networks to co-exist on the same spectrum without affecting the normal operation of the primary network [3]. In many existing cognitive satellite scenarios, satellite users which are considered as SUs can utilize unused terrestrial spectrum to expand their system capacity [4].

The main functions of CR system are spectrum awareness and spectrum exploitation [5]. Spectrum sensing technique is one of the most common spectrum awareness techniques, and this technique needs SUs to communicate by spectral holes that are not occupied by Primary Users (PUs). Under non-ideal spectrum sensing, the probability that the SU does not detect that the PU is occupying the channel during communication must be considered. Therefore, link interference of SUs to PUs cannot be ignored under non-ideal spectrum sensing [6], [7]. In satellite terrestrial hybrid scenarios with non-ideal spectrum sensing, power allocation algorithm is introduced to optimize the effective capacity of the terrestrial link for the given Quality of Service (QoS) requirements [8]. A practical link decision algorithm is proposed to improve transmission performance over a Rayleigh fading channel [9]. CR principles can be used for satellite communications. Sagduyu and Shi et al. presented a game theoretic framework based on regret minimization for satellite communication with PU and SU operating in the presence of cognitive interferers. This framework supports spectrum sharing and dynamic spectrum access over multiple channels [10]–[12].

Spectrum exploitation is an essential capability for CR system to allocate available resources optimally for SUs [5], [13], [14]. It is significant for cognitive satellite system to allocate resources efficiently [15]–[17]. Shi et al. presented optimal power control schemes in cognitive satellite terrestrial networks. The numerical results demonstrate the outage probability of satellite user decreases with the increasing of peak interference power and becomes saturated once peak interference power limit is large enough [15]. Lagunas *et al.* [16] focused on the microwave frequency bands and proposed a joint power and carrier allocation strategy to maximize the satellite total throughput. Maleki et al. studied the potential of applying cognitive radio techniques in Ka band satellite communications. CR techniques could act as a dynamic protection of SUs network from PUs interference [17]. The secure communication was investigated in cognitive satellite-terrestrial network [18]–[22]. Lin *et al.* [18]–[20] proposed two beamforming schemes to solve resource optimization problem in different case of eavesdroppers with high computational efficiency. Lin *et al.* [20] and Li *et al.* [21], [22] minimized the transmit power of satellite-terrestrial networks to enhance the security of the satellite link, and a secure and robust beamforming framework was presented. However, these existing methods do not address the problem of the satellite users' resource allocation based on the end-to-end communication delay. End-to-end delay is represented as the quality scale of the whole link. Resource optimization makes more sense when considering the quality of the whole link. It is an urgent challenge to investigate appropriate end-to-end delay optimization algorithm for actual propagation channels in cognitive satellite terrestrial networks.

In this investigation, we propose an algorithm to allocate satellite terrestrial network resources considering about link interference. A possible coexistence scenarios for satellite terrestrial networks is presented, and the proposed algorithm is aim to minimize satellite system's end-to-end delay of transmitting data. Compared with traditional studies, the end-to-end performance of transport-layer is considered. In addition, numerical results validate the performance enhancement of the proposed algorithm under non-ideal spectrum sensing.

The rest of this paper is organized as follows. Section II introduces the system model, and the problem formulation is presented in Section III. A joint resource allocation algorithm is proposed to solve the problem for the cases of non-ideal spectrum sensing in Section IV. Section V illustrates the numerical results, followed by conclusions in Section VI.

II. SYSTEM MODEL

In this section, we describe the considered cognitive satellite-terrestrial architecture. Fig. 1 shows the cognitive satellite terrestrial networks scenario. Let PU=$\{\mathrm{PU}_j|\mathrm{PU}_1, \mathrm{PU}_2,\ldots, \mathrm{PU}_N\}$ to describe the terrestrial terminals, and SU=$\{\mathrm{SU}_i|\mathrm{SU}_1, \mathrm{SU}_2, \ldots, \mathrm{SU}_M\}$ is the satellite terminals. The different kinds of satellite users act as SUs and terrestrial users represent PUs in the cognitive satellite-terrestrial network. The secondary system consists of SUs and satellites. Satellite users can share the same spectrum with terrestrial users by spectrum sensing technology for the uplink case. We assume the whole system is integrated and users can transmit data over multiple RATs. So the satellite users are allowed to transmit whenever terrestrial users do not occupy a specific band.

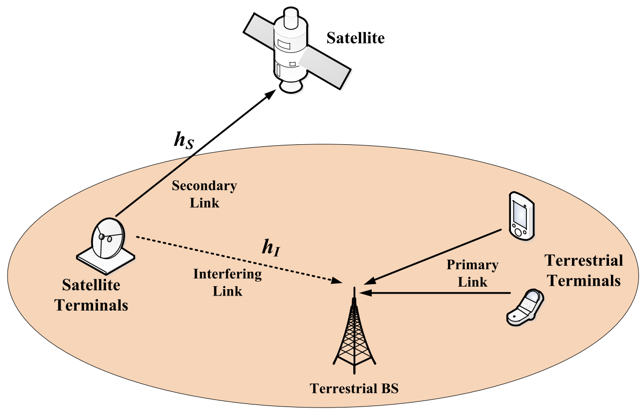


FIGURE 1. The scenario of cognitive satellite terrestrial networks.

As shown in Fig. 1, h_S and h_I represent channel power gains of the second link and the interfering link, respectively. In addition, the interference from terrestrial users to satellite can be negligible due to the far distance [6]. For the terrestrial links, Nakagami fading distribution are considered, and the probability density (pdf) function of interfering channel power gains is given by [23]:

$$f_{h_I}(h_I) = \frac{\varepsilon^{m_I} h_I^{m_I-1}}{\Gamma(m_I)} \exp(-\varepsilon h_I) \tag{1}$$

where m_I is Nakagami fading parameter, $\Gamma(\cdot)$ is the Gamma function, $\varepsilon = m_I/\Omega_I$ and Ω_I is average power of the line-of-sight component, namely $E(h_I) = \Omega_I$. As for satellite links, Shadowed Rician fading channels are adopted. The pdf of satellite channel power gains is given by [24]:

$$f_{h_S}(h_S) = \alpha \exp(-\beta h_S)\, {}_1F_1(m_S, 1, \delta h_S) \tag{2}$$

where ${}_1F_1(\cdot, \cdot, \cdot)$ denotes the confluent hypergeometric function [25], $\beta = 1/2b_S$, $\alpha = [2b_S m_S/(2b_S m_S + \Omega_S)]^{m_S}/2b_S$, $\delta = \Omega_S/[2b_S(2b_S m_S + \Omega_S)]$. $2b_S$ is the average power of the scatter component, Ω_S is average power and m_S is Nakagami fading parameter. In addition, we suppose m_S takes on integer values. According to [24] we rewrite (2) as

$$f_{h_S}(h_S) = \frac{\alpha \sum_{k=0}^{m_S-1} \frac{(-1)^k (1-m_S)_k (\delta h_S)^k}{(k!)^2}}{\exp((\beta-\delta)h_S)} \tag{3}$$

where $(x)_n = x(x+1)\cdots(x+n-1)$ is the Pochhammer symbol. Besides, it is assumed that both h_S and h_I are available based on the ideal channel state information (CSI).

Satellite users' communication is interrupted by PUs, and the arrival of PUs is described by PU activity matrix (ϕ) model, which improves system throughput performance compared with Poisson model [26]. The PU's average channel idle time is equal to the reciprocal of the mean of the activity matrix. Therefore, the maximum transmission time of the SU is equal to the maximum idle time of the PU channel [27]:

$$T = \frac{1}{E(\phi)} \tag{4}$$

III. PROBLEM FORMULATION

In this section, the resource allocation problem of satellite terrestrial networks are investigated for the cases of non-ideal spectrum sensing scenario. B_j is the available bandwidth of RAT$_j$, and B_{ij} is the bandwidth allocated to SU$_i$ by RAT$_j$. P_i represents the total power of the SU$_i$, and P_{ij} is the power allocated by SU$_i$ to transmit data simultaneously through RAT$_j$ [14]. D_i denotes total data transmitted by SU$_i$, and D_{ij} is the data that SU$_i$ transport through RAT$_j$. I_j is interference tolerance of PU$_j$, and I_{ij} is interference of SU$_i$ to PU$_j$. $i = 1, 2, \ldots, M, j = 1, 2, .., N$. The problem is formulated as:

$$\begin{aligned}
&\min f(B_{ij}, P_{ij}, D_{ij}) = \sum_{i=1}^{M} t_i = \sum_{i=1}^{M} (\max_j t_{ij})\\
&s.t.\ \sum_{i=1}^{M} B_{ij} \le B_j,\\
&\quad \sum_{j=1}^{N} P_{ij} \le P_i,\\
&\quad \sum_{j=1}^{N} D_{ij} = D_i,\\
&\quad \sum_{i=1}^{M} I_{ij} \le I_j,\\
&\quad B_{ij}, P_{ij}, \quad D_{ij} \ge 0\\
&\quad xi = 1, 2, \ldots, M, \quad j = 1, 2, \ldots, N
\end{aligned} \tag{5}$$

where t_i is the total time that SU$_i$ sends D_i through multiple RATs, and t_{ij} donates the time to transport data by RAT$_j$.

$$t_{ij} = \frac{D_{ij}}{C_{ij}} + \Delta t_{ij} \tag{6}$$

In (6) C_{ij} represents channel capacity of RAT$_j$ that SU$_i$ used, Δt_{ij} is the time delay caused by the arrival of PU$_j$ during SU$_i$ communication [26], [27]:

$$\Delta t_{ij} = \frac{D_{ij}}{C_{ij}(1/E[\phi_j])} \cdot \frac{1}{E[1-\phi_j]} = \frac{D_{ij}}{C_{ij}} \cdot \frac{E[\phi_j]}{E[1-\phi_j]} \tag{7}$$

where $E[\phi_j]$ is the expectation of PU$_j$ activity matrix, and let $k_j = E[\phi_j]/E[1-\phi_j]$. From Shannon capacity formula, channel capacity C_{ij} is:

$$C_{ij} = B_{ij} \log_2(1 + \frac{h_s P_{ij}}{N_s}) \tag{8}$$

where h_S is satellite channel power gain and N_s is noise power.

When the SU does not detect that the PU is occupying the channel during communication, interference would be caused to the PU [7]. When both PU$_j$ and SU$_i$ occupy the channel, SU's interference to the PU$_j$ is:

$$I_{ij} = \eta_{ij} h_I P_{ij}, \tag{9}$$

where η_{ij} is the probability of missed detection and h_I represent the channel power gains of interfering link. To reduce interference with the primary user, it is expected that the SU's interference to the PU is within the interference tolerance (I_j) of PU while the missed detection occurs.

IV. THE SOLUTION FOR THE PROBLEM

In this section, the convexity of the objective function is discussed, and the optimal algorithm is proposed to solve the problem of resource allocation in cognitive satellite terrestrial networks.

A. THE PROOF OF THE CONCAVITY

To prove that the objective function in (5) is a convex function, the objective function is simplified as follows:

$$f(B, P, D) = \frac{D}{B \ln(1+P)} \tag{10}$$

The leading principal submatrices of Hessian is

$$\det(H_1) = \frac{2D}{B^3 \ln(1+P)} \ge 0 \tag{11a}$$

$$\det(H_2) = \frac{D^2[3 + 2\ln(1+P)]}{(1+P)^2 B^4 \ln^4(1+P)} \ge 0 \tag{11b}$$

$$\det(H_3) = \frac{-D(1+C)}{(1+P)^2 B^5 \ln^5(1+P)} < 0 \tag{11c}$$

Because the Hessian matrix is not a positive or negative semi definite matrix, the *f(B,D,P)* is neither convex nor concave. To solve the problem, searching for the optimal solution of B_{ij} and P_{ij} with given $\overline{D}_{ij}$, then searching for the optimal solution of D_{ij} with given $\overline{B}_{ij}$ and $\overline{P}_{ij}$.

Under given $\overline{D}_{ij}$, the above problem is formulated as:

$$\begin{aligned}
&\min f(B_{ij}, P_{ij}) = \sum_{i=1}^{M} t_i = \sum_{i=1}^{M} t_i(\max_j t_{ij})\\
&s.t.\ \sum_{i=1}^{M} B_{ij} \le B_j,\\
&\quad \sum_{j=1}^{N} P_{ij} \le P_i,\\
&\quad \sum_{i=1}^{M} I_{ij} \le I_j,
\end{aligned}$$

$$\begin{aligned}&B_{ij} \quad , P_{ij} \geq 0\\&i=1,2,\ldots,M, j=1,2,\ldots,N\end{aligned} \tag{12}$$

The objective function can be simplified as follows:

$$f(B,P)=\frac{\overline{D}}{B\ln(1+P)}, \tag{13}$$

The Hessian is:

$$H=\nabla^2 f=\overline{D}\times\begin{pmatrix}\dfrac{2}{B^3\ln(1+P)} & \dfrac{1}{(1+P)B^2\ln^2(1+P)}\\ \dfrac{1}{(1+P)B^2\ln^2(1+P)} & \dfrac{2+\ln(1+P)}{(1+P)^2B\ln^3(1+P)}\end{pmatrix} \tag{14}$$

The leading principal submatrices of Hessian is:

$$\det(H_1)=\frac{2\overline{D}}{B^3\ln(1+P)}\geq 0 \tag{15a}$$

$$\det(H_2)=\frac{\overline{D}^2[3+2\ln(1+P)]}{(1+P)^2B^4\ln^4(1+P)}\geq 0 \tag{15b}$$

The result of (15) is obtained from the constraints $B_{ij}\geq 0$ and $P_{ij}\geq 0$. From the above calculations the function *f(B,P)* is convex.

B. THE OPTIMAL SOLUTION FOR THE PROBLEM

To find the optimal solution of (12), the Lagrangian is defined as below:

$$\begin{aligned}L(B_{ij},P_{ij},\omega_j,\upsilon_i,\gamma_j)=&\frac{\overline{D}(1+k_j)}{B_{ij}\log_2(1+\frac{h_SP_{ij}}{N_s})}\\&+\sum_{j=1}^{N}\omega_j(\sum_{i=1}^{M}B_{ij}-B_j)\\&+\sum_{i=1}^{M}\upsilon_i(\sum_{j=1}^{N}P_{ij}-P_i)\\&+\sum_{j=1}^{N}\gamma_j(\sum_{i=1}^{M}\eta_{ij}h_IP_{ij}-I_j)\end{aligned} \tag{16}$$

where ω_j, υ_i and γ_j are nonnegative Lagrange multipliers. The Karush-Kuhn-Tucker (KKT) conditions are as follows [28]:

$$\frac{\partial L}{\partial B_{ij}}=\frac{-\overline{D}(1+k_j)}{B_{ij}^2\log_2(1+\frac{h_SP_{ij}}{N_s})}+\omega_j=0 \tag{17}$$

$$\begin{aligned}\frac{\partial L}{\partial P_{ij}}=&\frac{-\overline{D}(1+k_j)h_S}{B_{ij}(N_s+h_SP_{ij})\log_2^2(1+\frac{h_SP_{ij}}{N_s})}\\&+\upsilon_i+\gamma_j\eta_{ij}h_I=0\end{aligned} \tag{18}$$

$$\omega_j(\sum_{i=1}^{M}B_{ij}-B_j)=0,\quad \sum_{i=1}^{M}B_{ij}-B_j\leq 0 \tag{19}$$

$$\upsilon_i(\sum_{j=1}^{N}P_{ij}-P_i)=0,\quad \sum_{j=1}^{N}P_{ij}-P_i\leq 0 \tag{20}$$

$$\gamma_j(\sum_{i=1}^{M}\eta_{ij}h_IP_{ij}-I_j)=0,\quad \sum_{i=1}^{M}\eta_{ij}h_IP_{ij}-I_j\leq 0 \tag{21}$$

We can get solution of bandwidth and power allocation B_{ij} and P_{ij} from system of nonlinear equations (17) and (18):

$$\begin{cases}y_1(B_{ij},P_{ij})=\dfrac{\partial L}{\partial B_{ij}}=0\\ y_2(B_{ij},P_{ij})=\dfrac{\partial L}{\partial P_{ij}}=0\end{cases} \tag{22}$$

To find the optimal value of B_{ij} and P_{ij}, the Newton's method is applied for faster convergence rate. Using the binary Taylor expansion at B_{ij}^k and P_{ij}^k, and choosing the linear part:

$$\begin{cases}\dfrac{\partial y_1(B_{ij}^k,P_{ij}^k)}{\partial B_{ij}}\Delta B_{ij}^k+\dfrac{\partial y_1(B_{ij}^k,P_{ij}^k)}{\partial P_{ij}}\Delta P_{ij}^k=-y_1(B_{ij}^k,P_{ij}^k)\\ \dfrac{\partial y_2(B_{ij}^k,P_{ij}^k)}{\partial B_{ij}}\Delta B_{ij}^k+\dfrac{\partial y_2(B_{ij}^k,P_{ij}^k)}{\partial P_{ij}}\Delta P_{ij}^k=-y_2(B_{ij}^k,P_{ij}^k)\end{cases} \tag{23}$$

where k represents the k^{th} iteration. ΔB_{ij}^k and ΔP_{ij}^k are calculated from (23), then we can get:

$$\begin{cases}B_{ij}^{k+1}=B_{ij}^k+\Delta B_{ij}^k\\ P_{ij}^{k+1}=P_{ij}^k+\Delta P_{ij}^k\end{cases} \tag{24}$$

The iteration stops when $\max(\Delta B_{ij},\Delta P_{ij})<\varepsilon$. To update the ω_j^k, υ_i^k and γ_j^k, we consider the following equation:

$$F(\omega_j,\upsilon_i,\gamma_j)=\max_{B,P}L(B_{ij},P_{ij},\omega_j,\upsilon_i,\gamma_j). \tag{25}$$

Using gradient method, the updated value of ω_j^{k+1} is obtained:

$$\begin{aligned}\omega_j^{k+1}&=[\omega_j^k-\varsigma\frac{\partial F(\omega_j,\upsilon_i,\gamma_j)}{\partial\omega_j^k}]^+\\&=[\omega_j^k-\varsigma(\sum_{i=1}^{M}B_{ij}^k-B_j)]^+\end{aligned} \tag{26}$$

where $\varsigma>0$ is a constant step size of the iteration, and $[z]^+=\max\{z,0\}$. In the same way, the updated value of υ_i and γ_j can also be calculated by

$$\begin{aligned}\upsilon_i^{k+1}&=[\upsilon_i^k-\xi\frac{\partial F(\omega_j,\upsilon_i,\gamma_j)}{\partial\upsilon_i^k}]^+\\&=[\upsilon_i^k-\xi(\sum_{j=1}^{N}P_{ij}^k-P_i)]^+\end{aligned} \tag{27}$$

$$\begin{aligned}\gamma_j^{k+1}&=[\gamma_j^k-\zeta\frac{\partial F(\omega_j,\upsilon_i,\gamma_j)}{\partial\gamma_j^k}]^+\\&=[\gamma_j^k-\zeta(\sum_{i=1}^{M}\eta_{ij}h_IP_{ij}^k-I_j)]^+\end{aligned} \tag{28}$$

where $\xi,\zeta>0$ are constant step size of the iteration.

Using $\overline{B_{ij}}$ and $\overline{P_{ij}}$ calculated above, the problem to find the optimal value of D_{ij} can be changed into how to allocate data to minimize the transported delay under given channel capacity. According to (6)-(8), the transported delay is

$$t_{ij} = \frac{D_{ij}}{\overline{C}_{ij}} + \Delta t_{ij} = (k_j + 1)\frac{D_{ij}}{\overline{C}_{ij}} \tag{29}$$

$$\overline{C}_{ij} = \overline{B}_{ij} \log_2(1 + \frac{h_S \overline{P}_{ij}}{N_s}) \tag{30}$$

In the case of known channel capacity, the transported delay through multiple RATs is the shortest if the transported delay of each RAT is the same:

$$\begin{cases} (k_j + 1)\dfrac{D_{ij}}{\overline{C}_{ij}} = t_0 \\ \displaystyle\sum_{j=1}^{N} D_{ij} = D_i \end{cases} \tag{31}$$

where t_0 is the same transported delay through multiple RATs. So we can get solution of transported data from (31):

$$D_{ij} = \frac{\overline{C}_{ij} D_i}{(k_j + 1) \sum_{j=1}^{N} \frac{\overline{C}_{ij}}{(k_j+1)}}. \tag{32}$$

Algorithm 1 The Joint Resource Allocation Algorithm

1: Initialize $\overline{D}_{ij}$, B_{ij}^0, P_{ij}^0, ω_j^0, υ_i^0 and γ_j^0;
2: Set $k = 0$;
3: **repeat**
4: Calculate B_{ij}^{k+1} and P_{ij}^{k+1} using Newton's method by (24);
5: **if** $\max(\Delta B_{ij}, \Delta P_{ij}) < \varepsilon$, **then**
6: Calculate D_{ij} with B_{ij}^{k+1} and P_{ij}^{k+1} by (31);
7: Break;
8: **else**
9: Update ω_j^{k+1} with B_{ij}^{k+1} using gradient method by (26);
10: Update υ_i^{k+1} and γ_j^{k+1} with P_{ij}^{k+1} using gradient method by (27) and (28);
11: $k = k + 1$;
12: **end if**
13: **return** D_{ij}, B_{ij}^{k+1} and P_{ij}^{k+1};

C. THE JOINT RESOURCE ALLOCATION ALGORITHM

According to the analysis of the optimal solution for problem in Section IV.B, we propose a distributed joint allocation method and the steps are shown in Algorithm 1. At first initialize the system parameters B_{ij}^0, P_{ij}^0 and Lagrange multipliers ω_j^0, υ_i^0, γ_j^0. Then by the iterative of Newton's method, the better approximation values of B_{ij}^{k+1} and P_{ij}^{k+1} can be calculated with given $\overline{D}_{ij}$. After B_{ij}^{k+1} and P_{ij}^{k+1} is obtained, D_{ij} can be determined by (31). In addition, from the KKT conditions the values of Lagrange multipliers are updated using gradient based method.

The time complexity of the proposed algorithm is dependent on the number of iterations. For Algorithm 1, it takes $O(K)$ times to converge, which is a typically small number. K is defined as the number of iterations when the proposed algorithm converges. Considering the number of SUs and RATs, we can derive the total time complexity of distributed joint allocation algorithm is $O(KMN)$.

V. NUMERICAL RESULTS

In this section, numerical results validate the performance enhancement of proposed algorithm and the impact of channel condition parameters on SUs' delays are presented. The channel power gains of terrestrial links and satellite links are assumed to be unit mean [9]. The parameters of the simulation are listed in TABLE 1. It is assumed that 3 SUs use 2 RATs to transmit data.

TABLE 1. Parameters of the simulation.

Parameters of the Simulation	Values
Noise power N_s	5dBm
Precision requirement ε	1×10^{-5}
Number of SUs	3
Number of RATs	2
Probability of missed detection η	0.04

Three shadowing scenarios of the satellite links are employed, namely, Infrequent Light Shadowing (ILS), Frequent Heavy Shadowing (FHS) and Average Shadowing (AS). The typical parameters of the satellite scenarios are obtained from [29] and are listed in TABLE 2.

TABLE 2. Typical parameters of the satellite scenarios.

Shadowing Scenarios	b_S	m_S	Ω_S
ILS	0.158	19.1	1.29
FHS	0.063	0.739	8.97×10^{-4}
AS	0.126	10.1	0.835

In Figure 2, we set the bandwidth of RATs as 10MHz and 20MHz, SUs' power is 40mW, and the interference tolerance is 0.08mW. We consider $\overline{D}_{ij} = 150$Mbits before resource allocation, and the transmitted data of SU_i is 300Mbits. For the terrestrial links the fading parameters are $\Omega_I = m_I = 1$. Comparing the delay before and after resource allocation, delay gain is defined as the percent that the delay performance could be improved, and is expressed as follow:

$$delay\ gain = \frac{d_1 - d_2}{d_1} \tag{33}$$

where d_1 is the delay before resource allocation and d_2 is the delay after resource allocation. As shown in Figure 2, the delay gain could be higher with the increase of $\mathrm{E}[\phi_j]$ under different shadowing scenarios. It is concluded that the larger $\mathrm{E}[\phi_j]$ is, the better transmission delay performance of satellite

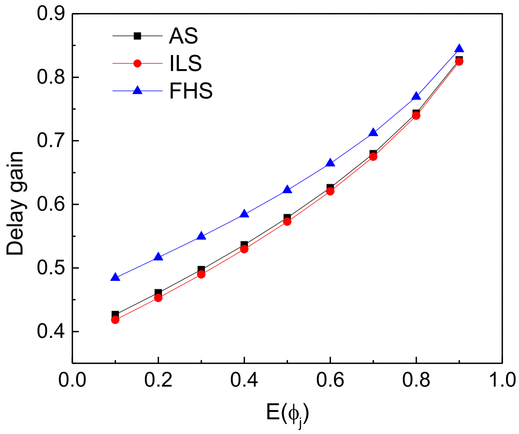


FIGURE 2. **The percent that the delay performance could be improved after resource allocation.**

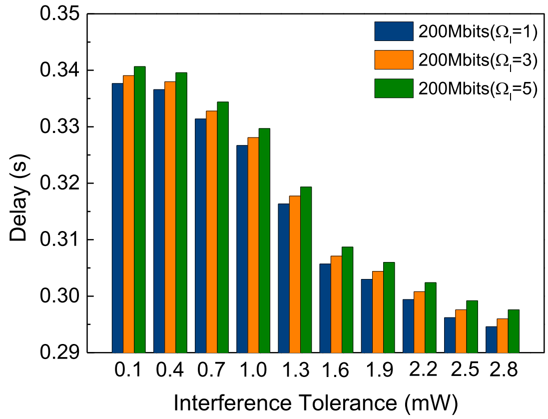


FIGURE 4. **The relationship between delays and interference tolerance.**

links is improved. The delay gain is different under different satellite channel shadow scenarios. The results indicate that the effect of the delay improvement is not only related to the PU activity matrix, but also to the shadowing scenario of the satellite channel (i.e., the value of the h_S).

Figure 3 presents the delays of satellite links versus E[ϕ_j] for different spectrum sensing conditions. The ILS is considered for the satellite links and the fading parameters are $\Omega_I = m_I = 1$ for the terrestrial links. SUs' power is set as 40mW, and the bandwidth of RATs is set as 10MHz and 20MHz respectively. The interference tolerance is 0.08mW, and SUs transmitted data is set as 300Mbits. As shown in Figure 3, the system delay rises with the E[ϕ_j] increasing. The channel idle time becomes shorter as E[ϕ_j] increases, so the time occupied by SU decreases and the system delay rises. The SUs transmission delays reduce by 42.63%-81.31% after the resource allocating under non-ideal spectrum sensing. However, compared with ideal spectrum sensing condition, the delays of satellite links would rise with the increase of E[ϕ_j] under non-ideal spectrum sensing. It is found that the proposed algorithm can improve delay performance obviously.

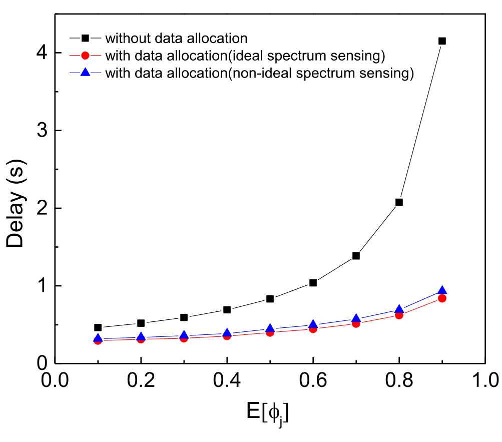


FIGURE 3. **The relationship between delays and E[ϕ_j].**

Figure 4 depicts the delays of satellite links versus I_j for different average of interfering channel power gains, where the ILS is considered for the satellite links. If the SU's interference to the PU is within the interference tolerance (I_j) of PU, then PU can transmit data normally. We set the bandwidth of RATs as 10MHz and 20MHz, and SUs' power as 40mW, and E[ϕ_j] of RATs is assumed as 0.4 and 0.8. SUs transmitted data is assumed to be 200Mbits, 400Mbits and Ω_I various from 1 to 5. It can be seen in Figure 4 that with the increase of interference tolerance, the delays of transmitting data gradually decrease. If the interference tolerance is higher, the anti-interference ability of the PUs will be stronger, and the SUs delay performance tends to be ideal spectrum sensing. In addition, when the value of Ω_I changes from 1 to 3 and from 3 to 5, the delays increase by 0.42% and 0.48%, respectively. It is because of the fact that the interfering link becomes stronger with the increase of Ω_I. Therefore, increasing Ω_I of the interference channel would cause the increase in transmission delays of SUs.

Fig. 5 shows the delays of satellite links versus transmitting data by SUs with AS and FHS shadowing scenarios of the satellite links. We consider the bandwidth of RATs as 10MHz and 30MHz, SUs' power is 40mW, and the interference tolerance is 0.08mW. E[ϕ_j] of RATs is set to be 0.4 and 0.8, and SUs transmitted data changes from 100Mbits to 1000Mbits. From Fig. 5 the values of delays increase nonlinearly when the transmitting data of SUs is higher. When the transmission data is 100Mbits, the delays of the FHS and the AS shadowing scenario are almost similar; however, as the transmission data increases to 1000Mbits, the delay of the FHS shadowing scenario is 0.02s smaller than that of the AS shadow scenario. In conclusion, the shadowing scenario of the satellite channel can also affect the delay of transmission data.

The relationship between delays and transmitting data by SUs after resource allocation is shown in Figure 6. The shadowing scenario of the satellite links is set as FHS and other parameters are the same as those in Fig. 5. The performance of system delay is improved better with the increase of transmission data. As the value of transmission data rises

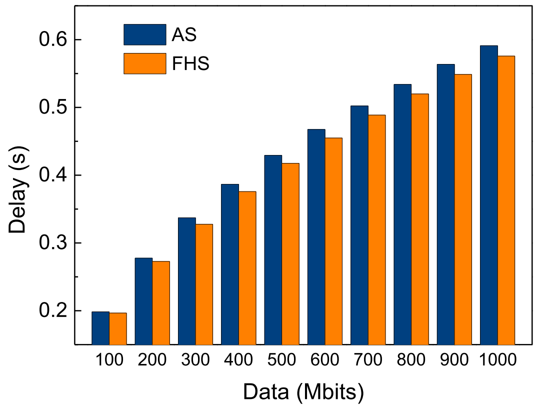


FIGURE 5. System delays with different transmitting data by SUs.

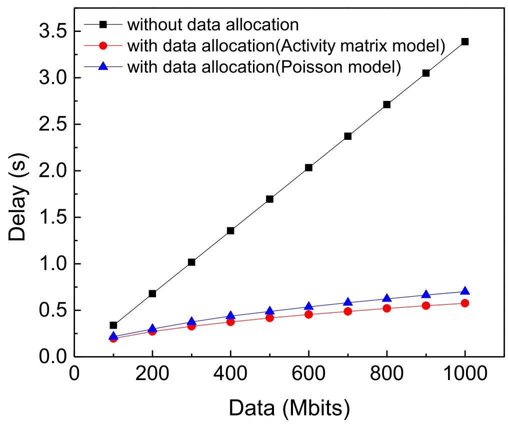


FIGURE 6. The delay improvement with different transmitting data after resource allocation.

to 1000Mbits, the system delay of proposed algorithm is reduced by 82.89%. Chen *et al.* [13] proposed step-by-step iterative algorithm based on Poisson model to minimize the delay of heterogeneous cognitive wireless networks. It can be found that as the transmission data is 800Mbits, the proposed algorithm based on PU activity matrix model is superior to the algorithm based on Poisson model. In other words, the proposed algorithm reduces the delay by 13.53% compared to the algorithm in [13]. In addition, when the transmission data various from 100Mbits to 1000Mbits, the system delay without data allocation increases linearly, but system delay increases nonlinearly after data allocation.

VI. CONCLUSION

In this paper, we introduce a possible coexistence scenarios for cognitive satellite terrestrial hybrid networks, and an algorithm based on convex optimization is proposed to allocate network resources under non-ideal spectrum sensing, which aims to minimize SU's end-to-end delay of transmitting data. We investigate the bandwidth allocation, power distribution and data transportation in cognitive satellite terrestrial network. Numerical results show that transmission delay performance is improved obviously after resource allocation. Under different shadowing scenarios the percent of delay reduction rises with the E[ϕ_j] increasing. And SUs delay performance tends to be ideal spectrum sensing when the interference tolerance is higher. The delay increases nonlinearly with the increase of transmission data, and the performance of system delay could be improved when transmission data is higher. Our results will provide useful reference in designing cognitive satellite terrestrial system. In future works, we will investigate the multi-objective optimization under different shadowing scenarios.

REFERENCES

[1] K. An *et al.*, "Performance analysis of multi-antenna hybrid satellite-terrestrial relay networks in the presence of interference," *IEEE Trans. Commun.*, vol. 63, no. 11, pp. 4390–4404, Nov. 2015.
[2] P. Chini, G. Giambene, and S. Kota, "A survey on mobile satellite systems," *Int. J. Satell. Commun. Netw.*, vol. 28, no. 1, pp. 29–57, Jan. 2010.
[3] S. K. Sharma, S. Chatzinotas, and B. Ottersten, "Cognitive radio techniques for satellite communication systems," in *Proc. IEEE VTC-Fall*, Las Vegas, NV, USA, Sep. 2013, pp. 1–5.
[4] M. Höyhtyä, J. Kyröläinen, A. Hulkkonen, J. Ylitalo, and A. Roivainen, "Application of cognitive radio techniques to satellite communication," in *Proc. IEEE Symp. Dyn. Spectr. Access Netw.*, Bellevue, WA, USA, Oct. 2012, pp. 540–551.
[5] S. Haykin, "Cognitive radio: Brain-empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.
[6] S. K. Sharma, S. Chatzinotas, and B. Ottersten, "Satellite cognitive communications: Interference modeling and techniques selection," in *Proc. 6th ASMS Conf. 12th SPSC Workshop*, Baiona, Spain, Sep. 2012, pp. 111–118.
[7] K. Liu, Q. Zhao, and B. Krishnamachari, "Dynamic multichannel access with imperfect channel state detection," *IEEE Trans. Signal Process.*, vol. 58, no. 5, pp. 2795–2808, May 2010.
[8] S. Vassaki, M. I. Poulakis, A. D. Panagopoulos, and P. Constantinou, "Power allocation in cognitive satellite terrestrial networks with QoS constraints," *IEEE Commun. Lett.*, vol. 17, no. 7, pp. 1344–1347, Jul. 2013.
[9] X. Tan, H. Zhang, and J. Hu, "Link decision algorithm in underlay cognitive radio networks over a Rayleigh fading channel," *IET Commun.*, vol. 8, no. 5, pp. 607–615, Mar. 2014.
[10] Y. E. Sagduyu, S. Yi, A. B. MacKenzie, and Y. T. Hou, "Regret minimization-based robust game theoretic solution for dynamic spectrum access," in *Proc. IEEE CCNC*, Las Vegas, NV, USA, Jan. 2016, pp. 200–205.
[11] Y. E. Sagduyu, Y. Shi, A. B. MacKenzie, and Y. T. Hou, "Regret minimization for primary/secondary access to satellite resources with cognitive interference," *IEEE Trans. Wireless Commun.*, vol. 17, no. 5, pp. 3512–3523, May 2018.
[12] Y. Shi and Y. E. Sagduyu, "Spectrum learning and access for cognitive satellite communications under jamming," in *Proc. IEEE Conf. Commun. Netw. Secur.*, Philadelphia, PA, USA, Oct. 2016, pp. 472–479.
[13] F. Chen, W.-J. Xu, J.-R. Lin, K. Niu, and H.-Y. Ma, "End-to-end utility-based resource allocation for multi-RAT nodes in heterogeneous cognitive wireless networks," *J. China Univ. Posts Telecommun.*, vol. 20, no. 2, pp. 19–24, Apr. 2013.
[14] Y. Choi, H. Kim, S.-W. Han, and Y. Han, "Joint resource allocation for parallel multi-radio access in heterogeneous wireless networks," *IEEE Trans. Wireless Commun.*, vol. 9, no. 11, pp. 3324–3329, Nov. 2010.
[15] S. Shi, G. Li, K. An, Z. Li, and G. Zheng, "Optimal power control for real-time applications in cognitive satellite terrestrial networks," *IEEE Commun. Lett.*, vol. 21, no. 8, pp. 1815–1818, Aug. 2017.
[16] E. Lagunas, S. K. Sharma, S. Maleki, S. Chatzinotas, and B. Ottersten, "Resource allocation for cognitive satellite communications with incumbent terrestrial networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 1, no. 3, pp. 305–317, Sep. 2015.
[17] S. Maleki *et al.*, "Cognitive spectrum utilization in Ka band multibeam Satellite communications," *IEEE Commun. Mag.*, vol. 53, no. 3, pp. 24–29, Mar. 2015.
[18] M. Lin, Z. Lin, W.-P. Zhu, and J.-B. Wang, "Joint beamforming for secure communication in cognitive satellite terrestrial networks," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 5, pp. 1017–1029, May 2018.

[19] Z. Lin, M. Lin, J.-B. Wang, Y. Huang, and W.-P. Zhu, "Robust secure beamforming for 5G cellular networks coexisting with satellite networks," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 4, pp. 932–945, Apr. 2018.

[20] Z. Lin, M. Lin, J. Ouyang, W.-P. Zhu, and S. Chatzinotas, "Beamforming for secure wireless information and power transfer in terrestrial networks coexisting with satellite networks," *IEEE Signal Process. Lett.*, vol. 25, no. 8, pp. 1166–1170, Aug. 2018.

[21] B. Li, Z. Fei, X. Xu, and Z. Chu, "Resource allocations for secure cognitive satellite terrestrial networks," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 78–81, Feb. 2018.

[22] B. Li, Z. Fei, Z. Chu, F. Zhou, K.-K. Wong, and P. Xiao, "Robust chance-constrained secure transmission for cognitive satellite-terrestrial networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 5, pp. 4208–4219, May 2018.

[23] M. K. Simon and M. S. Alouini, *Digital Communications Over Fading Channels*. New York, NY, USA: Wiley, 2005.

[24] K. An *et al.* "Secure transmission in cognitive satellite terrestrial networks," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 11, pp. 3025–3037, Nov. 2016.

[25] I. S. Gradshteyn and I. M. Ryzhik, *Table of Integrals, Series, and Products*, 7th ed. Amsterdam, The Netherlands: Elsevier, 2007.

[26] S. Shi, N. Liang, and X. Gu, "A resource allocation method of heterogeneous wireless cognitive networks based on convex optimization theory," in *Proc. 4th Int. Conf. IMCCC*, Harbin, China, Sep. 2014, pp. 139–144.

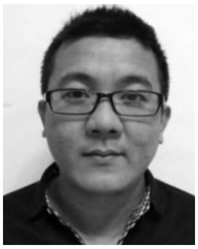
[27] B. Canberk, I. F. Akyildiz, and S. Oktug, "Primary user activity modeling using first-difference filter clustering and correlation in cognitive radio networks," *IEEE/ACM Trans. Netw.*, vol. 19, no. 1, pp. 170–183, Feb. 2011.

[28] S. Boyd and L. Vandenberghe, *Convex Optimization*. Cambridge, U.K.: Cambridge Univ. Press, 2004.

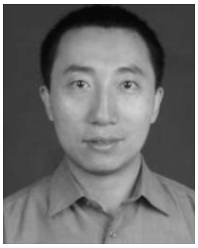
[29] A. Abdi, W. C. Lau, M.-S. Alouini, and M. Kaveh, "A new simple model for land mobile satellite channels: First- and second-order statistics," *IEEE Trans. Wireless Commun*, vol. 2, no. 3, pp. 519–528, May 2003.

WEILONG WANG received the bachelor's degree from the Beijing University of Aeronautics and Astronautics, in 2014, and the master's degree from Air Force Engineering University, Xi'an, China, in 2016, where he is currently pursuing the Ph.D. degree. His current research interests include optical inter-satellite communication, optical communication networks, and high-speed optical inter-satellite communication.

SHANGHONG ZHAO received the bachelor's and master's degrees from the Physics Department, Lanzhou University, Lanzhou, China, in 1984 and 1989, respectively, and the Ph.D. degree from the Xi'an Institute of Optics and Precision Mechanics, CAS, in 1998. He is currently a Full Professor with Air Force Engineering University, Xi'an, China. He is also the Head of the Space-Based Information Network Research Center. He has authored over 300 academic articles and four books. His teaching interests include the fields of space-based information networks, quantum key distribution, microwave photonics, and optoelectronics.



YONGXING ZHENG received the bachelor's degree in communication engineering from the PLA University of Science and Technology, in 2003, and the master's degree in military communication from Xidian University, in 2011. He is currently pursuing the Ph.D. degree with Air Force Engineering University, Xi'an, China. He is also a Researcher with the National Key Laboratory of Science and Technology on Space Microwave, China Academy of Space Technology. His research interests include the optical satellite networks, high-speed optical inter-satellite communication, and satellite network management.



YONGJUN LI received the bachelor's, master's, and Ph.D. degrees from Air Force Engineering University, Xi'an, China, in 2002, 2005, and 2009, respectively. He is currently an Associate Professor with Air Force Engineering University. He has authored over 30 academic articles and one book. His current research interests include the optical satellite networks, on-board optical signal processing, and satellite constellation design.