IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received September 8, 2019, accepted September 23, 2019, date of publication September 26, 2019,
date of current version October 17, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2943908

Efficient and Fair Resource Allocation Scheme for Cognitive Satellite-Terrestrial Networks

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This work was supported in part by the National Natural Science Foundation of China under Grant 61901502, and in part by the Research Project of the National University of Defense Technology (NUDT) under Grant ZK18-02-11.

ABSTRACT In this paper, we consider the resource allocation problem in uplink cognitive satellite-terrestrial networks, where the cognitive satellite users reuse the frequency band of terrestrial cellular networks. In this scenario, the joint radio resource allocation strategy has to be reasonably designed to satisfy the interference constraint required by the incumbent terrestrial network (ITN). We formulate the optimization model of joint resource allocation with the perspective of efficiency and fairness, where the interference constraint is defined as the maximum tolerable interference outage probability of the ITN. Then, we simplify the proposed optimization problem into a tractable convex optimization form by some necessary mathematical simplification, wherein the simplification of the probability constraint takes the outdated channel state information into account. By analyzing the conditions of the optimal solution for the joint resource allocation problem in detailed, we derive the closed-form expression for both power allocation and subchannel allocation. Besides, we design an iterative algorithm for the joint resource allocation based on these closed-form solutions. Finally, some supporting results are given to verify the correctness and efficiency of the proposed algorithm.

INDEX TERMS Cognitive satellite terrestrial networks, resource allocation, outdated channel state information, convex optimization.

I. INTRODUCTION

Satellite communications have been widely applied due to its capability of providing high-speed transmission rate and seamless coverage [1]–[5]. Satellite networks are expected to be an indispensable part of the upcoming 5G+ networks, which can form a complementation to the terrestrial network for achieving connection anytime and anywhere. However, with the rapidly increasing of satellite broadband services, the licensed spectrum granted for exclusive use in satellite networks has become increasingly scarce [6]. Such contradiction limits the capacity performance improving for the integrated satellite-terrestrial networks [7]. Fortunately, by incorporating the cognitive radio (CR) into the satellite network, spectrum sharing between satellite and terrestrial networks is expected to be a significant potential solution to address this unprecedented communication capacity demands [8].

In order to realize spectrum sharing between satellite and terrestrial networks, there are various promising network architectures that have been investigated by academic research and industry sectors [9]–[11]. In the concept of the cognitive satellite terrestrial network (CSTN), one popular architecture for uplink scenario is to consider the satellite system as the secondary network and employ the terrestrial system as the primary network [1], [3], [11]–[14]. Actually, Lagunas *et al.* [1] investigated the problem of joint resource allocation in CSTN for both the uplink and downlink cases, while Lagunas *et al.* [12] analyzed a set of optimized frameworks for multi-objective optimization problem in CSTN. Differently, Shi *et al.* [13] studied the optimal power control schemes for the uplink scenario of CSTN with both average and peak interference power constraints, respectively. An optimal power control scheme for the uplink CSTN with imperfect channel

The associate editor coordinating the review of this manuscript and approving it for publication was Ding Xu.

state information and the outage probability constraint was investigated in [14]. Similarly, Gao *et al.* [3] proposed an ADMM-based optimal power control scheme for the uplink scenario of CSTN with the consideration of average interference power constraint and interference outage probability constraint. Additionally, in order to mitigate the interference caused by spectrum sharing between the satellite and terrestrial networks, Vazquez *et al.* [11] proposed an analog beamforming technique to optimize the beamforming matrix design. However, to achieve secure transmission under interference-limited scenario, Li *et al.* [15] and [16] proposed that the interference generated from the terrestrial network can be served as an artificial noise by a suitable beamforming design, and then it can be used to protect the information of the satellite network from eavesdropping by illegal users. Moreover, representative works focused on performance analysis of CSTN have been discussed in [17]–[19] for various key performance merits.

It should be noted that the works mentioned above mostly concentrated on one-dimensional resource allocation. Although the only work in [1] included joint power and carriers allocation, but the objective for maximizing throughput of the cognitive network ignored the fairness among different users. While the Zhong *et al.* [7] considered joint power and bandwidth allocation for cognitive satellite network, it neglected the imperfect channel state information (CSI) of satellite networks. In actuality, since the channel estimation errors and the longtime feedback delay inevitably exist in satellite networks, the precise CSI of mutual interference link between the satellite and terrestrial networks is generally unavailable [20]. In this regard, it is necessary to study the joint resource allocation scheme in CSTN with the consideration of imperfect CSI.

In this paper, with the objective of maximizing the efficiency of resource utilization and pursuing the fairness among different users, we investigate the joint power and subchannel allocation problem for the uplink scenario of CSTN. Herein, the outdated CSI of the interference link from satellite user to the primary network and the maximum tolerable interference outage probability have been taken into consideration. The main contributions of this paper are summarized as follows:

- With the trade-off between efficiency and fairness, we formulate a novel optimization model for joint power and subchannel allocation in the uplink scenario of CSTN, which considers the maximum tolerable interference outage probability constraint in the presence of outdated CSI of interference link. The conditions of the optimal solution for the joint resource allocation problem have been provided based on necessary mathematical transformation.
- We derive the closed-form expression for power allocation based on the conditions of the optimal solution when subchannels assignment is given. And then we obtain the optimal strategy for subchannel allocation according to different subchannel assignment assumption and the optimal power allocation of each assumption.

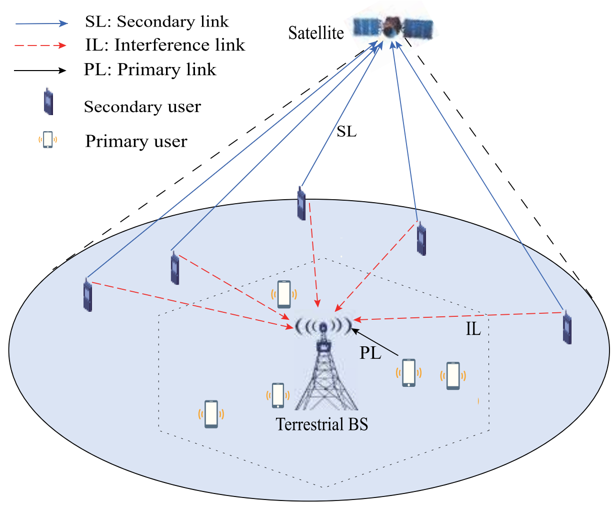

FIGURE 1. **Uplink spectrum sharing scenario for multiuser of cognitive satellite-terrestrial networks.**

- Based on the closed-form solution of power allocation and subchannel allocation, we propose a joint power and subchannel allocation algorithm to provide the execution structure for the optimization process. Then briefly discuss the complexity of the proposed algorithm, and detailedly validate the effectiveness of it by numerical simulations.

The rest of the paper is organized as follows. The system model of the considered CSTN is presented in Section II. In Section III, we formulate an optimization model for joint resource allocation and analyze the conditions of the optimal solution. In Section IV we derive out the closed-form solutions of power allocation and subchannel allocation and design an algorithm for joint resource allocation. In Section V, numerical results and discussions are presented. Finally, the conclusion of this paper is given in Section VI.

II. SYSTEM MODEL

In this paper, we consider the uplink CSTN where the cognitive satellite users reuse the frequency band of terrestrial cellular networks, which are the incumbent system in the S-band on 2.5-2.6 GHz [3]. Notice that, such frequency band considered in this paper just is used as an example for analyzing the spectrum sharing in cognitive satellite-terrestrial networks. Of course, other bands such as L-band and C-band can be used for similar analysis. Schematically, the considered scenario can be depicted as Fig.1. In this hybrid network, there are M primary terrestrial users (PTUs) occupying K subchannels through orthogonal frequency division multiple access (OFDMA) paradigm to transmit their uplink signals to the base station (BS) [21], and N secondary satellite users (SSUs) sharing the same band of the terrestrial network to transmit their uplink signals to the geostationary (GEO) satellite with frequency division multiple access (FDMA) scheme [1]. Throughout this paper, we assume the subchannels of the satellite network are divided by the same way as the terrestrial network, which means that there are K subchannels in the satellite network. Moreover, we assume one subchannel only can be used by one SSU at the same time. To achieve fairness in resource allocation for multiple users while without considering the scheduling among different users, it is necessary to assume that the number of subchannels is greater than the number of secondary satellite users, i.e., $K > N$, in this paper.

Herein, let $\mathcal{N} = \{1, 2, \cdots, N\}$ denotes the set of all SSUs, and $\mathcal{K} = \{1, 2, \cdots, K\}$ denotes the set of all subchannels. For simplification of analysis, we assume all terminals considered in this work are equipped with a single antenna [22]. Then, we can use $h_{n,k}$ and $g_{n,k}$ $(n \in \mathcal{K}, k \in \mathcal{N})$ to denote the channel power gain of the secondary link (SL) from nth SSU to the GEO satellite on subchannel k and the channel power gain of the interference link (IL) from nth SSU to the BS on subchannel k, respectively. Indeed, all of the channel power gains depicted in this work aggregate the transmit antenna gain, propagation loss, receive antenna gain and fading channel coefficient. We assume that all SLs obey independent and identically distributed (i.i.d.) block Rician fading, while all ILs obey i.i.d. block Nakagami-m fading [22]. More about link budget analysis can be referred to [17], [19], [23]. It should be noted that the weak interference from PTUs to the GEO satellite is neglected due to the limited transmission power versus the long transmission distance [8]. Let $p_{n,k}$ denotes the transmit power of SSU n on subchannel k, and $\mathbf{P} = \left[p_{n,k}\right]_{N\times K}$ is the power allocation matrix for all SSUs. Similarly, let $\mathbf{\Delta} = \left[\delta_{n,k}\right]_{N\times K}$ denotes the subchannel allocation matrix for all SSUs, where $\delta_{n,k} = 1$ means that subchannel k is assigned to SSU n, and $\delta_{n,k} = 0$ otherwise.

According to the denotations mentioned above, the received signal-to-noise ratio (SNR)at the GEO for SSU n on the kth subchannel is given by

$$\gamma_{n,k} = \frac{p_{n,k}h_{n,k}}{\sigma^2}. \tag{1}$$

Based on Shannon's capacity formula, the transmission rate achieved by SSU n on the kth subchannel can be given as

$$r_{n,k} = \log_2\left(1 + \frac{\gamma_{n,k}}{\Upsilon}\right), \tag{2}$$

where $\Upsilon = -\ln(5\text{BER})/1.5$ is bit error rate (BER) gap between the channel capacity and the practical transmission rate implemented by a given modulation and coding scheme [24]. Then, the achievable rate of SSU n can be defined as

$$R_n = \sum_{k=1}^{K} \delta_{n,k} r_{n,k}. \tag{3}$$

On the other hand, due to the spectrum sharing between the satellite network and terrestrial cellular networks, the interference impact to the BS on the subchannel k consists with

$$I_k = \sum_{n=1}^{N} \delta_{n,k} p_{n,k} g_{n,k}. \tag{4}$$

To protect the performance of the primary terrestrial network, the interference caused by SSUs at BS must satisfy the following constraint

$$I_k \le I_k^{th}, \tag{5}$$

where I_k^{th} represents the tolerable interference threshold of BS on subchannel k. However, when considering the large propagation in satellite system, the exact CSI of IL from SSUs to BS is difficult to be known by the network control center (NCC) of satellite system. Practically, the NCC is more likely to obtain the outdated CSI of IL rather than instantaneous CSI in the transmission process. According to the work in [25], an estimated channel gain model based on outdated CSI can be given by

$$\sqrt{g_{n,k}} = \rho\sqrt{\hat{g}_{n,k}} + \sqrt{1-\rho^2}\sqrt{\tilde{g}_{n,k}}, \tag{6}$$

where $g_{n,k}$ and $\hat{g}_{n,k}$ denote the current and outdated channel power gain of IL, respectively. $\tilde{g}_{n,k}$ represents a Nakagami-m random valuable with unit variance, which is i.i.d. with $\hat{g}_{n,k}$. The correlation coefficient between the current and outdated block is given by $\rho = J_0(2\pi f_d \tau)$, where $J_0(\cdot)$ is the zero-order Bessel function of the first kind, f_d is the Doppler spread and τ is the block duration.

Considering the channel model based on outdated CSI, we try to introduce a modified interference constraint condition for the uplink scenario of CSTN, which is defined as

$$\Pr\left\{I_k > I_k^{th}\right\} \le \varepsilon_k, \tag{7}$$

where ε_k denotes the maximum tolerable outage probability of primary terrestrial network on subchannel k.

III. PROBLEM FORMULATION AND BASIC OPTIMIZATION ANALYSIS

A. PROBLEM FORMULATION

Taking the efficiency and fairness into account in resource allocation, we aim to find an optimized scheme to balance the efficiency with fairness in resource allocation of the satellite network. Therefore, we define the efficient and fair resource allocation problem as maximizing the sum of the logarithmic transmission rate for all SSUs. Then the optimization problem can be formulated as follows

$$(\text{P1}): \max_{\mathbf{P},\mathbf{\Delta}} U = \sum_{n=1}^{N} \ln R_n, \tag{8a}$$

$$\text{subject to: } \Pr\left\{I_k > I_k^{th}\right\} \le \varepsilon, \quad \forall k \in \mathcal{K}, \tag{8b}$$

$$\sum_{k=1}^{K} \delta_{n,k} p_{n,k} \le p_n^{\max}, \quad \forall n \in \mathcal{N}, \tag{8c}$$

$$\sum_{n=1}^{N} \delta_{n,k} \leq 1, \quad \forall k \in \mathcal{K}, \tag{8d}$$

$$\delta_{n,k} \in \{0, 1\}, \quad \forall n \in \mathcal{N}, \ \forall k \in \mathcal{K}, \tag{8e}$$

$$p_{n,k} \geq 0, \quad \forall n \in \mathcal{N}, \ \forall k \in \mathcal{K}, \tag{8f}$$

where $p_n^{\max}$ denotes the maximum available transmission power of SSU n. It should be noted that, the fairness of the optimization problem (P1) refers to the proportional fairness defined in [24], and it is given in definition 1. The meaning of the optimization problem (P1) for fairness and efficiency would be analyzed in the next subsection.

Definition 1: The rates distribution is proportionally fair if it satisfies that any change in the distribution of the rates results in the sum of the proportional changes of the utilities being nonpositive, i.e.,

$$\sum_{n=1}^{N} \frac{R_n - \tilde{R}_n}{\tilde{R}_n} \leq 0, \tag{9}$$

where $\tilde{R}_n$ and R_n are the the proportionally fair rate distribution and any other feasible rate distribution for the user n, respectively.

B. BASIC OPTIMIZATION ANALYSIS

Obviously, the proposed optimization problem (P1) in the previous subsection is hard to be solved because it needs to deal with the mixed integer nonlinear programming problem and also involves the probability constraint. We try to transform it into a tractable form and analyze the optimal conditions of the transformed form in this subsection. Even the probability constraint in (8b) is a complex combination constraint and highly non-linear, however, combining the equation (4) with the constraints of (8d) and (8e), the constraint (8b) can be transformed into the equivalent form as

$$\Pr\left\{\delta_{n,k} p_{n,k} g_{n,k} > I_k^{th}\right\} \leq \varepsilon, \quad \forall n \in \mathcal{N}, \ \forall k \in \mathcal{K}. \tag{10}$$

Assume the subchannel k is allocated to SSU n, in this case, the constraint (10) can be rewritten as

$$\Pr\left\{g_{n,k} > \frac{I_k^{th}}{p_{n,k}}\right\} \leq \varepsilon. \tag{11}$$

According to the channel gain model depicted in equation (6) and the cumulative distribution function (CDF) of channel power gain in nakagami-m fading channel [26], we can get the following lemma 1.

Lemma 1: While the outdated channel power gain $\hat{g}_{n,k}$ can be known, the constraint (11) is equivalent to

$$p_{n,k} \leq \frac{I_k^{th}}{\left(\sqrt{F_{\tilde{g}_{n,k}}^{-1}(1-\varepsilon)\left(1-\rho^2\right)} + \rho\sqrt{\hat{g}_{n,k}}\right)^2 \Big|_{\hat{g}_{n,k}}}, \tag{12}$$

where $F_{\tilde{g}_{n,k}}^{-1}(\cdot)$ is the inverse CDF of $\tilde{g}_{n,k}$. Here, the CDF of $\tilde{g}_{n,k}$ is defined as [3]

$$F_{\tilde{g}_{n,k}}(z) = \frac{\gamma\left(m_k, \frac{m_k}{\Omega_k} z\right)}{\Gamma(m_k)}, \tag{13}$$

where m_k represents the fading severity parameter, Ω_k denotes the average power of the channel coefficient, and $\gamma(\alpha, z) = \int_0^z t^{\alpha-1} e^{-t} dt$ represents the lower incomplete Gamma function, $\Gamma(s) = \int_0^\infty t^{s-1} e^{-t} \mathrm{d}t$ denotes the Gamma function.

Proof: See Appendix A.

Since the subchannel k and the SSU n analyzed above are arbitrary in $\mathcal{K}$ and $\mathcal{N}$, respectively, hence the constraint (10) is equivalent to

$$p_{n,k} \leq \frac{I_k^{th}}{\varphi(\varepsilon, \rho)\big|_{\hat{g}_{n,k}}}, \quad \forall n \in \mathcal{N}, \ \forall k \in \mathcal{K}, \tag{14}$$

where $\varphi(\varepsilon, \rho) = \left(\sqrt{F_{\tilde{g}_{n,k}}^{-1}(1-\varepsilon)}\left(1-\rho^2\right) + \rho\sqrt{\hat{g}_{n,k}}\right)^2$.

Based on the analysis mentioned above, the probability constraint for (P1) is converted to a linear constraint. However, since the discrete constraint (8e) exists, the problem (P1) is still a non-convex problem. Fortunately, it can be tackled by relaxing the discrete variable $\delta_{n,k}$ into a continuous range [21], so long as the final solution takes the boundary value of the continuous range. Consequently, we rewrite the constraint of $\delta_{n,k}$ as

$$0 \leq \delta_{n,k} \leq 1. \tag{15}$$

Now, the proposed optimization problem (P1) can be reformulated as

$$\begin{aligned} \text{(P2)}: \ & \max_{\mathbf{P},\boldsymbol{\Delta}} U = \sum_{n=1}^{N} \ln R_n \\ & \text{subjectto}: (14), (8c), (8d), (15), (8f). \end{aligned} \tag{16}$$

Theorem 1: The problem (P2) is a convex optimization problem.

Proof: See Appendix B.

Now, based on *Definition 1* and *Theorem 1* as well as the Nash bargaining game theory [27], we can get the following corollary.

Corollary 1: The optimal solution of (P2) is proportionally fair and Pareto optimal.

Proof: The optimization objective function in (P2) can be transformed into the equivalent form as

$$\max_{\mathbf{P},\Delta} U = \prod_{n=1}^{N} (R_n - 0), \tag{17}$$

According to *Theorem 1*, R_n is concave in its constraint set. Let $\mathbf{R} = (R_1, \cdots, R_n, \cdots, R_N)$, $\mathbf{R}^{\min} = (0)_{1\times N}$, and then the pair of $\left(\mathbf{R}, \mathbf{R}^{\min}\right)$ constructs a N-player bargaining game. From the Nash bargaining game theory, there exists an unique Nash bargaining solution (NBS) of the optimization problem (P2). By define the $\hat{U}_n = \ln(R_n)$, the gradient of $\hat{U}_n$ at the NBS point $\tilde{R}_n$ is $\left(\partial \hat{U}_n / \partial R_n\right)|_{\tilde{R}_n}$. Since the NBS point optimizes (P2), for any point deviating from the NBS point, the following optimality condition holds:

$$\sum_{n=1}^{N} \left(\partial \hat{U}_n / \partial R_n\right)|_{\tilde{R}_n} \left(R_n - \tilde{R}_n\right) = \sum_{n=1}^{N} \frac{R_n - \tilde{R}_n}{\tilde{R}_n} \leq 0. \tag{18}$$

The equation (18) means the optimal solution $\tilde{R}_n$ satisfies the *Definition 1*, so it is proportionally fair. Additionally, since the optimal solution of (P2) is a special case of NBS, so it is Pareto optimal. The proof is complete.

In addition, according to *Theorem 1*, herein we solve the problem (P2) by choosing the Lagrange multiplier method to integrate the constraints into the dual problem [28]. By applying the dual method, the Lagrange function of the optimization problem(P2) can be defined as

$$L\left(\mathbf{P}, \boldsymbol{\Delta}, \boldsymbol{\lambda}, \boldsymbol{\mu}\right) = \sum_{n=1}^{N} \ln R_n + \sum_{n=1}^{N} \lambda_n \left(p_n^{\max} - \sum_{k=1}^{K} \delta_{n,k} p_{n,k}\right) + \sum_{k=1}^{K} \mu_k \left(1 - \sum_{n=1}^{N} \delta_{n,k}\right), \quad (19)$$

where $\boldsymbol{\lambda} = [\lambda_n]_{N\times 1}$ and $\boldsymbol{\mu} = [\mu_k]_{K\times 1}$ are non-negative Lagrangian multipliers associated with the constraint (8c) and (8d), respectively. Then, the dual problem is given by

$$\min_{\lambda,\mu} \max_{\mathbf{P},\boldsymbol{\Delta}} L\left(\mathbf{P}, \boldsymbol{\Delta}, \lambda, \mu\right). \quad (20)$$

It is noticeable that the boundary constraints (14), (15) and (8f) will be absorbed in the Karush-Kuhn-Tucker (KKT) conditions [29], which can be explained as follows. Denote $p^*_{n,k}$ and $\delta^*_{n,k}$ as the optimal solution for $1 \le k \le K$, $1 \le n \le N$. Let $p'_{n,k} = \frac{I_k^{th}}{\varphi(\varepsilon,\rho)|_{\hat{g}_{n,k}}}$. According to the KKT conditions, there are the following necessary and sufficient conditions for $p^*_{n,k}$ and $\delta^*_{n,k}$:

$$\frac{\partial L\left(\cdots\right)}{\partial p^*_{n,k}} \begin{cases} \le 0, & p^*_{n,k} = 0 \\ = 0, & 0 < p^*_{n,k} < p'_{n,k} \\ \ge 0, & p^*_{n,k} = p'_{n,k}, \end{cases} \quad \forall k, n \quad (21)$$

$$\frac{\partial L\left(\cdots\right)}{\partial \delta^*_{n,k}} \begin{cases} \le 0, & \delta^*_{n,k} = 0 \\ = 0, & 0 < \delta^*_{n,k} < 1 \\ \ge 0, & \delta^*_{n,k} = 1, \end{cases} \quad \forall k, n \quad (22)$$

$$\lambda_n^* \left(p_n^{\max} - \sum_{k=1}^{K} \delta^*_{n,k} p^*_{n,k}\right) = 0 \quad (23)$$

$$\mu_k^* \left(1 - \sum_{n=1}^{N} \delta^*_{n,k}\right) = 0 \quad (24)$$

IV. EFFICIENT AND FAIR RESOURCE ALLOCATION SCHEME DESIGN

In this section, we first solve the joint radio resource allocation problem (P2) by giving the closed-form solution of two subproblems of power allocation and subchannel allocation. And then, an algorithm is designed based on subchannel assignment assumption to provide the execution structure for joint power and subchannel allocation.

A. OPTIMAL POWER ALLOCATION

In this subsection, we derive the closed-form solution for the optimal power allocation when subchannels assignment is given. For the sake of analysis, we firstly give the partial derivative of the Lagrange function in (19) with respect to $p_{n,k}$ as

$$\frac{\partial L\left(\cdots\right)}{\partial p_{n,k}} = \left(\frac{1}{R_n} \frac{h'_{n,k}}{\ln 2\left(1 + p_{n,k} h'_{n,k}\right)} - \lambda_n\right) \delta_{n,k}. \quad (25)$$

Herein, the $h'_{n,k}$ in (25) is defined as $h'_{n,k} \triangleq \frac{h_{n,k}}{\sigma^2 \Upsilon}$. Intuitively, for any $1 \le k \le K$ and $1 \le n \le N$, if $\delta_{n,k} \ne 1$, $p^*_{n,k} = 0$. Thus, we only need to consider the case that $\delta_{n,k} = 1$ for the equation (25). For any $\delta_{n,k} = 1$, the optimal power allocation results can be divided into the following situations for analyzation.

Case 1: $\lambda = 0$, based on the optimal condition (23) in the previous subsection, there exists $\frac{\partial L(\cdots)}{\partial p_{n,k}} > 0$. So that, the Lagrange function $L\left(\mathbf{P}, \boldsymbol{\Delta}, \boldsymbol{\lambda}, \boldsymbol{\mu}\right)$ is increasing monotonously respect to $p_{n,k}$, and $p^*_{n,k} = p'_{n,k}$.

Case 2: $\lambda > 0$, the optimal condition (23) requires that $\left(p_n^{\max} - \sum_{k=1}^{K} \delta_{n,k} p_{n,k}\right) = 0$. Thus, from $\frac{\partial L(\cdots)}{\partial p_{n,k}} = 0$, we can get it that the extreme point of $L\left(\mathbf{P}, \boldsymbol{\Delta}, \boldsymbol{\lambda}, \boldsymbol{\mu}\right)$ respect to $p_{n,k}$ is

$$p''_{n,k} = \left[\frac{1}{\ln 2 \lambda_n R_n} - \frac{\sigma^2}{g_{n,k}}\right]^+, \quad (26)$$

where $[x]^+ = \max(0, x)$. Equation (26) shows that the potential optimal power allocation follows the water-filling approach. Here, $\frac{1}{\ln 2\lambda_n R_n}$ is the water level which can be solved by a recursive search with the constraint that [24]

$$\sum_{k=1}^{K} \delta_{n,k} p_{n,k} = p_n^{\max}. \quad (27)$$

Combining the equation (26) and the constraint (14), the optimal power allocation results can be given by

$$p^*_{n,k} = \min\left\{p'_{n,k}, p''_{n,k}\right\}. \quad (28)$$

For a given subchannel assignment and a given Lagrange multipliers vector $\boldsymbol{\lambda}$, the closed-form solution of the optimal power allocation results can be given by the above analysis, i.e.

$$p^*_{n,k} = \begin{cases} 0, & \delta_{n,k} = 0 \\ p'_{n,k}, & \delta_{n,k} = 1, \lambda_n = 0 \\ \min\left\{p'_{n,k}, p''_{n,k}\right\}, & \delta_{n,k} = 1, \lambda_n = 1. \end{cases} \quad (29)$$

B. OPTIMAL SUBCHANNEL ALLOCATION

The previous subsection has discussed the closed-form solution of the optimal power allocation for a given subchannel assignment. In this subsection, we try to derive the optimal strategy for subchannel allocation based on different subchannel assignment assumption and the optimal power allocation of each assumption.

Similar to the previous subsection, we give the partial derivative of the Lagrange function in (19) with respect to $\delta_{n,k}$ as

$$\frac{\partial L\left(\cdots\right)}{\partial \delta_{n,k}} = \frac{1}{R_n} r_{n,k} - \lambda_n p_{n,k} - \mu_k. \quad (30)$$

When considering an arbitrary subchannel should be allocated to which SSU, there is no harm to suppose that the pending subchannel k will be allocated to every SSU. Based on this assumption, substituting the optimal power allocation (29) into (30) and applying the KKT condition (22), we can get that [7], [21]

$$\delta_{n,k}^{*}=\begin{cases}1, & n=\arg\max\limits_{n'} T_{n',k}\\ 0, & n\neq \arg\max\limits_{n'} T_{n',k}.\end{cases} \tag{31}$$

Herein, $T_{n',k}=\left(\frac{1}{R_{n'}}r_{n',k}-\lambda_{n',k}p_{n',k}\right)$, and the $p_{n',k}$ is calculated by (29) with the assumption that subchannel k has been allocated to SSU n'.

Now, according to the formula (26) and (28), we can see that the optimal strategy for power allocation and subchannel allocation is correlative. For this regard, it is hard to say which part of the resource is efficient and fair, while the efficiency and fairness should be reflected by the joint power and subchannel allocation.

Whether from the optimal power allocation result of (29) or the optimal subchannel assignment strategy of (31), we can see that only the Lagrangian multipliers $\boldsymbol{\lambda}=[\lambda_n]_{N\times 1}$ associate to the optimal resource allocation scheme. To obtain the optimal solution for the dual problem (20), we try to find the best Lagrangian multipliers by using the subgradient method to update the dual variables. Similar to the method in [21], the updating way for Lagrangian multipliers can be given as follows

$$\lambda_{n,k}^{(l+1)}=\left[\lambda_{k,i}^{(l)}-\beta^{(l)}\left(P_n^{\max}-\sum_{k=1}^{K}\delta_{n,k}p_{n,k}\right)\right]^{+},\quad \forall n,k, \tag{32}$$

where $\beta^{(l)}$ is the step size of the iteration l, which should satisfy the following constraint for converging to the optimal solution.

$$\sum_{l=1}^{\infty}\beta^{(l)}=\infty,\ \lim_{l\to\infty}\beta^{(l)}=0. \tag{33}$$

C. ITERATIVE ALGORITHM

From the previous two subsections, we have obtained the closed-form solution of power and subchannel allocation. However, it still requires to design an algorithm for the implementation of the solving process. Thus, we propose the Algorithm 1 as follows to implement the joint power and subchannel allocation for cognitive satellite network.

Note that the NCC of satellite network requires to know the I_k^{th} of each subchannel to execute the Algorithm 1. Such information can be obtained by SSUs' active sensing of the downlink feedback signals from BS, or the NCC directly obtains the I_k^{th} on each subchannel by cooperating with the terrestrial network. Additionally, since the sequence of the optimization process of subchannel allocation would affect the $T_{n,k}$ of each SSU, which would affect the allocation result of subchannel k for further, the ultima resource allocation results obtained by the proposed algorithm 1 might be approximate optimum. Moreover, the complexity of the algorithm 1 decides by the scale of the number of subchannels and the number of SSUs as well as the maximum iteration number, with an upper bound as $K\times N\times L_{\max}$. Such algorithm complexity is far less than the complexity of exhaustive search (N^K), especially when the scale of N and K is large.

Algorithm 1 Joint Power and Subchannel Allocation (JPSA) Algorithm for Cognitive Satellite Network

Initialization:
Initialize L_{max}, $\boldsymbol{\lambda}$, ε and p_n^{max} for any SSU n at first. Let $l=0$, and generate the random $\boldsymbol{\Delta}^{(l)}=\left[\delta_{n,k}^{(l)}\right]_{N\times K}$ and the random $\mathbf{P}^{(l)}=\left[p_{n,k}^{(l)}\right]_{N\times K}$ as the initial resource strategy that satisfies the constraints of (P1). Calculate the object function $U^{(l)}=\sum_{n=1}^{N}\ln R_n^{(l)}$ based on $\boldsymbol{\Delta}^{(l)}$ and $\mathbf{P}^{(l)}$.
Iteration Process:
repeat
  $l++$;
  for $k=1$ to K **do**
    for $n=1$ to N **do**
      a) Suppose the subchannel k is allocated to the SSU n, which means $\delta_{n,k}=1$. Then, for $\forall k'\in\mathcal{K}$, calculate the transmit power $p_{n,k'}$ of SSU n according to (29).
      b) Calculate the $T_{n,k}$ based on the power allocation results of step a).
    end for
    Update $\delta_{n,k}^{(l)}$ for all SSUs according to (31) and let $p_{n,k'}^{(l)}=p_{n,k'}$ for SSU n if and only if $\delta_{n,k}=1$.
    Calculate the object function $U^{(l)}=\sum_{n=1}^{N}\ln R_n^{(l)}$ based on $\boldsymbol{\Delta}^{(l)}$ and $\mathbf{P}^{(l)}$.
    Update $\boldsymbol{\lambda}$ according to (32).
  end for
until $U^{(l)}=U^{(l-1)}$ or $l>L_{\max}$.

V. SIMULATION RESULTS AND DISCUSSION

In this section, we present the numerical results to evaluate the performance of efficiency and fairness for proposed scheme in the cognitive satellite network resource allocation.

The simulation parameters of the considered system are set as: $K=10$, $N=5$, $p_n^{max}=5$W ($\forall n\in\mathcal{N}$), $\sigma^2=-130$dBw, $\Upsilon=2$, and the bandwidth for each subchannel k is $B_k=$ 1MHz, while the transmit antenna gain of SSUs and the receive antenna gain of the satellite refer to the setting in [3]. The parameters of terrestrial fading channel are chosen as: $m_k=5$ and $\Omega_k=1$, for all k, and $\rho=0.8$, while the Rician fading factor of the satellite link is chosen as 1. The initial Lagrangian multipliers vector of the algorithm 1 is set as $\boldsymbol{\lambda}=[1]_{N\times 1}$, and the step size for updating Lagrangian multipliers is set as $\beta^{(l)}=1/\left(l\cdot p_n^{\max}\right)$. Especially, we assume all SSUs and the considered BS are located in the area covered by

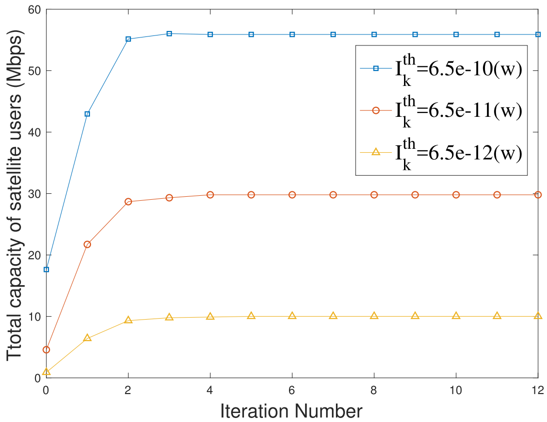

FIGURE 2. Convergence performance of the proposed algorithm.

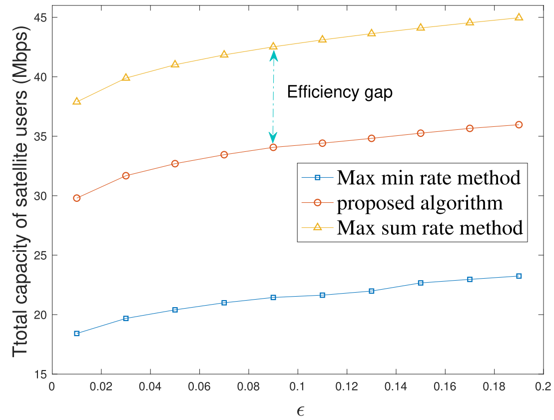

FIGURE 3. The evolutionary relationship between the total capacity of SSUs and the variable ϵ.

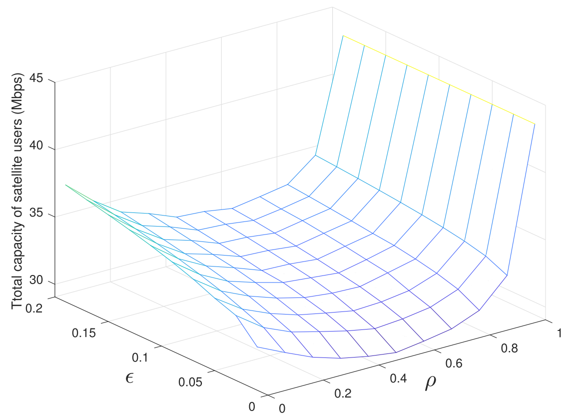

FIGURE 4. Total capacity verse ρ and ϵ.

the major lobe of the satellite, and all SSUs are uniformly distributed in the annular region with an inner radius of 2kM and an outer radius of 5kM centered on the BS. The numerical results given here are obtained by averaging 1000 rounds of Monte-Carlo simulations.

First of all, we verify the convergence of the proposed algorithm by using three different interference thresholds and the same outage probability for simulations as shown in Fig. 2. Herein, the interference thresholds are set as $I_k^{th} = 6.5 \times 10^{-10}$W, $I_k^{th} = 6.5 \times 10^{-11}$W and $I_k^{th} = 6.5 \times 10^{-12}$W, and the outage probability is chosen by $\varepsilon = 0.01$. As shown in Fig.2, the total capacity of the cognitive satellite network retains invariant after running 5 iterations of the proposed resource allocation scheme, which means the proposed resource allocation scheme is convergent. Additionally, although different capacities would be obtained by the proposed scheme for different interference constraints, the convergent speed is barely effected by different interference constraints. On the other hand, this fast convergence performance of the proposed scheme is fit for the outdated channel state information features of the satellite link, which further verifies the effectivity of our method. Moreover, the total capacity improves with the increase of interference threshold, and there is an obvious improvement for total capacity when reaching convergence. The above results validate the effectiveness of the proposed algorithm.

Subsequently, we compare the proposed algorithm with the maximum sum rate allocation in [30] and the max-min fairness allocation in [12]. Fig.3 shows that the total capacity obtained by different methods increases with the outage probability ε increases, wherein $I_k^{th} = 6.5 \times 10^{-11}$W. Moreover, compared to the maximum sum-rate method, the total capacity obtained by the proposed algorithm degraded limitedly, but the proposed method is significantly enhanced over than the max-min method.

Additionally, Fig. 4 plots the total capacity for all SSUs versus the outdated CSI correlation coefficient ρ and the interference outage probability ϵ of terrestrial primary network. We can see that the total capacity for all SSUs is increasing with respect to ϵ when $\epsilon \neq 1$, but it is invariable for $\epsilon = 1$. The reason for this result can be explained as follows. If $\rho = 1$, then $g_{n,k} = \hat{g}_{n,k}$, which means the resource allocation is independent to the uncertain part of $\tilde{g}_{n,k}$. With respect to ρ, the total capacity is decreasing when ρ is less than the inflection point, while monotonically increasing when ρ is greater than the inflection point. Such phenomenon can be explained as that $\hat{g}_{n,k}$ and $\tilde{g}_{n,k}$ are i.i.d., hence $\varphi(\varepsilon, \rho)$ increases with ρ increasing when it is greater than the inflection point, but decreases with ρ increasing when it is less than the inflection point.

Finally, Fig. 5 further compares the fairness index (FI) performance of the three different methods mentioned above, where the metric of fairness index can be defined as FI $\triangleq \left(\sum_{n=1}^{N} R_n\right)^2 / \left(N \sum_{n=1}^{N} R_n^2\right)$ [31]. It is observed that the max-min method obtained the optimal FI performance among all considered methods, while the FI obtained by our proposed algorithm is slightly smaller than the max-min method. However, the FI performance achieved by the maximum sum rate method is far less than it obtained by the previous two methods. Additionally, it is should be noticed that each fairness index performance curve changes slightly with the increase of the maximum tolerable outage probability of primary terrestrial network. The reason for this phenomenon can

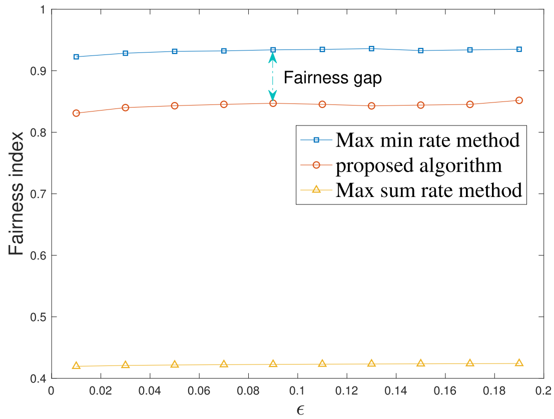

FIGURE 5. The evolutionary relationship between the fairness index and the variable ϵ.

be explained by the fact that the maximum tolerable outage probability ε is relevant to the strategy of optimal power allocation, and then in further affects the subchannel allocation in the considered network. Therefore, the resource allocation results for each method in the comparison simulation will change with the variation of ε.

VI. CONCLUSION

In this paper, we formulated the optimization model of joint resource allocation for CSTN from the perspective of efficiency and fairness, whose optimal solution has been proved to be proportionally fair and Pareto optimal. Specifically, the proposed optimization problem is transformed into a tractable convex optimization form by some necessary mathematical simplification, wherein the simplification of the probability constraint takes the outdated channel model into account. Then, we derive the closed-form solution for both power allocation and subchannel allocation, and design a JPSA algorithm based on these closed-form solution. Finally, numerical results including comparisons are given to verify the correctness and efficiency of the proposed algorithm. For the future work, as the MIMO and the relaying technology have been widely used in the hybrid satellite-terrestrial network, we will extend the proposed scheme to the MIMO or relay application scenario [32]–[35].

APPENDIX A
PROOF OF LEMMA 1

Based on the channel gain model depicted in (6) and the i.i.d. relation between $\hat{g}_{n,k}$ and $\tilde{g}_{n,k}$, we can obtain the follows equation about the joint probability density function (PDF) of $g_{n,k}$ and $\hat{g}_{n,k}$.

$$f_{g_{n,k},\hat{g}_{n,k}}(x, y) = f_{\tilde{g}_{n,k},\hat{g}_{n,k}}(z, y) = f_{\tilde{g}_{n,k}}(z) f_{\hat{g}_{n,k}}(y), \tag{34}$$

where $\sqrt{x} = \rho\sqrt{y} + \sqrt{1-\rho^2}\sqrt{z}$. Then the conditioned PDF of the $g_{n,k}$ for given the $\hat{g}_{n,k}$ can be obtained as

$$f_{g_{n,k}|\hat{g}_{n,k}}(x|y) = \frac{f_{\tilde{g}_{n,k},\hat{g}_{n,k}}(z, y)}{f_{\hat{g}_{n,k}}(y)} = f_{\tilde{g}_{n,k}}(z). \tag{35}$$

Based on the probability relation of contrary events, for given $\hat{g}_{n,k}$, from the constraint (11), we can get that

$$\Pr\left\{g_{n,k} > \frac{I_k^{th}}{p_{n.k}}\right\}|\hat{g}_{n,k} = 1 - \Pr\left\{g_{n,k} \le \frac{I_k^{th}}{p_{n.k}}\right\}|\hat{g}_{n,k} \le \varepsilon. \tag{36}$$

According to (35), the equation (39) can be further rewritten as

$$\begin{aligned}
&\Pr\left\{g_{n,k} \le \frac{I_k^{th}}{p_{n,k}}\right\}|\hat{g}_{n,k} \\
&= \int_0^{I_k^{th}/p_{n,k}} f_{g_{n,k}|\hat{g}_{n,k}}(x|y)\mathrm{d}x \\
&= \int_0^{\left(\sqrt{I_k^{th}/p_{n,k}} - \rho\sqrt{\hat{g}_{n,k}}\right)^2/(1-\rho^2)} f_{\tilde{g}_{n,k}}(z)\,\mathrm{d}z \\
&= F_{\tilde{g}_{n,k}}\left(\left(\sqrt{I_k^{th}/p_{n,k}} - \rho\sqrt{\hat{g}_{n,k}}\right)^2 / \left(1-\rho^2\right)\right)|\hat{g}_{n,k} \\
&\ge 1 - \varepsilon,
\end{aligned} \tag{37}$$

where $F_{\tilde{g}_{n,k}}(z)$ is the CDF of $\tilde{g}_{n,k}$. Since $F_{\tilde{g}_{n,k}}(z)$ is a strict monotonicly increasing function with respect to z, according to the equation (37) we can easily obtain that

$$p_{n,k} \le \frac{I_k^{th}}{\left(\sqrt{F^{-1}_{\tilde{g}_{n,k}}(1-\varepsilon)\left(1-\rho^2\right)} + \rho\sqrt{\hat{g}_{n,k}}\right)^2 |\hat{g}_{n,k}}. \tag{38}$$

Therefore, Lemma 1 is fully proved.

APPENDIX B
PROOF OF THEOREM 1

To prove (P2) is a convex optimization problem, it is necessary to prove that the constraints set of the optimization problem (P2) is convex and the objective function of (P2) is convex or concave.

Now, we denote $\mathbf{D}_2$ as the constraints set of (P2). Since all constraints of the optimization problem (P2) are linear, for any $0 \le \theta \le 1$, there have $\theta(\mathbf{P}^{(1)}, \mathbf{\Delta}^{(1)}) + (1-\theta)(\mathbf{P}^{(2)}, \mathbf{\Delta}^{(2)}) \in \mathbf{D}_2$, where $(\mathbf{P}^{(1)}, \mathbf{\Delta}^{(1)}) \in \mathbf{D}_2$ and $(\mathbf{P}^{(2)}, \mathbf{\Delta}^{(2)}) \in \mathbf{D}_2$. Hence, the constraints set $\mathbf{D}_2$ for (P2) is convex.

Additionally, since the objective function of (P2) is the sum of polynomials, if each term of the polynomial is convex (concave), the objective function is convex (concave). According to the formula (1)-(3) and the condition of logarithm operation, for any $(\mathbf{P}, \mathbf{\Delta}) \in \mathbf{D}_2$,there have $R_n > 0, \forall n \in \mathcal{N}$. Moreover, for any $1 \le n \le N$, the Hessian matrix of R_n

respects to $p_{n,k}$ and $\delta_{n,k}$ can be given as

$$\mathbf{H}\left(p_{n,k}, \delta_{n,k}\right) = \begin{pmatrix} \dfrac{\partial^2 R_n}{\partial p_{n,k}^2} & \dfrac{\partial^2 R_n}{\partial p_{n,k} \partial \delta_{n,k}} \\ \dfrac{\partial^2 R_n}{\partial p_{n,k} \partial \delta_{n,k}} & \dfrac{\partial^2 R_n}{\partial \delta_{n,k}^2} \end{pmatrix}$$
$$= \begin{pmatrix} \dfrac{-\delta_{n,k} h_{n,k}^2}{\ln 2\sigma^4 \Upsilon^2 \left(1 + \frac{p_{n,k} h_{n,k}}{\sigma^2 \Upsilon}\right)^2} & 0 \\ 0 & 0 \end{pmatrix}. \quad (39)$$

As the first element of $\mathbf{H}\left(p_{n,k}, \delta_{n,k}\right)$ is non-positive, it can conclude that $\mathbf{H}\left(p_{n,k}, \delta_{n,k}\right)$ is negative semidefinite. Hence, R_n is concave for any $1 \leq n \leq N$.

From $R_n > 0, \forall n \in \mathcal{N}$ and R_n is concave for any $1 \leq n \leq N$, we can know that R_n is a non-negative concave, which is equivalent to log-concave [28]. Therefore, for any $1 \leq n \leq N$, $\ln R_n$ is concave. Hence the objective function of the optimization problem (P2) is concave.

Now, Theorem 1 is completely proved.

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