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Joint Transmit Power and Bandwidth Allocation for Cognitive Satellite Network Based on Bargaining Game Theory

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ABSTRACT With the rapidly increasing spectrum demand by multimedia applications, the limitation of the spectrum resource restricts the improvement of the performance for communication systems. The cognitive spectrum utilization scenario can solve this problem by sharing the licensed spectrum of primary users (PUs) with secondary users under specific constrains. In this paper, we consider the uplink resource allocation problem in cognitive satellite network, where cognitive satellite users exploit the spectrum allocated to terrestrial networks as PUs. In order to control the interference to the PUs caused by cognitive users and achieve a fair allocation with considerable total capacity, we detailedly investigate the joint transmit power and bandwidth allocation problem with reasonable system model we proposed. We propose combined resource management architecture to improve computational efficiency, and formulate the resource allocation problem as a cooperative bargaining game based on game theory. The near optimal joint resource allocation is derived on dual domain of original problem, and a cooperative resource allocating algorithm is proposed based on subgradient method. From simulation results, several important concluding remarks are obtained as follows: 1) The proposed algorithm has a considerable convergence rate, and distributed computation can further improve computational efficiency; 2) The multi-user and multi-beam diversity can improve total capacity, while interference constrains and the limitation of resource limit the performance boundary; and 3) Compared with existing methods, the proposed algorithm is Pareto optimal, which can achieve a better tradeoff between fairness among users and total capacity of the whole network.

INDEX TERMS Cognitive satellite network, bargaining game, resource allocation, power control.

I. INTRODUCTION

Satellite communication is widely applied for it's high data transmission rate and wide-range of coverage [1], [2]. Satellite networks can be deployed to extend the coverage of terrestrial networks for remote areas, emergency communication and maritime scenario. However, the spectrum scare and growing demand of multimedia applications prevent the improve of performance for both satellite networks and terrestrial networks [3]. The cognitive radio (CR) technology seems to be a promising scheme to solve this problem, which allows satellite networks and terrestrial networks to reuse same spectrum resource to improve system utility with limited bandwidth resource [4], [5].

More recently, CR technology has become a hot topic for satellite communications reusing same spectrum resource with terrestrial systems. In order to realize cooperative communication between satellite networks and terrestrial networks, the technology of spectrum awareness has been investigated and developed for cognitive satellite networks [4]–[6]. The interference model between terrestrial and satellite system has been analyzed in [7] and [8]. Maleki *et al.* [8] determined geographical areas called cognitive zones where spectrum sensing technology should be applied to reduce the interference to PUs. Cooperative communication strategies for cognitive satellite networks are developed to improve the system capacity [9], [10]. In [9], the terrestrial users assisted satellite network to realize cooperative communication. Singh *et al.* [10] used a overlay approach to achieve effective cooperation between secondary transmitter with amplify-and forward based relays and PU. Some representative works concentrated on the performance analysis for cognitive satellite networks [11], [12], and the physical layer security problem of the networks has been discussed in [13] and [14]. With these enabling technologies, cognitive communication for hybrid satellite-terrestrial network can achieve stable and secure cooperation.

To achieve better exploitation of CR, resource allocation schemes is a promising mean to improve the spectrum efficiency under interference constrains. However, resource management method related to CR networks mostly concentrated on terrestrial networks [15]–[17]. Power control problems has been investigated to protect PUs with interference caused by SUs using the same bandwidth [18]–[23]. In [18], an underlay power control approach for cognitive satellite networks was proposed to satisfy the interference power constrains and interference outage probability constrains. An optimal power control scheme was investigated in [19] for cognitive satellite networks with imperfect channel state information to maximize the outage capacity of cognitive satellite users with communication guarantee for primary terrestrial users. Vassaki *et al.* [20] introduced a power allocation algorithm to improve the effective capacity of terrestrial networks while guaranteeing a specified out age probability of satellite networks. Shi *et al.* [21] investigated the power control problem for cognitive satellite networks with real-time service. In [22], some representative methods for power control in satellite networks were reviewed, and these methods were evaluate to the cognitive satellite networks. In [23], a power allocation solution was give to maximize the achievable rate of the cognitive satellite network. In [18]–[23], the spectrum resource was assumed to be allocated to users properly with reasonable strategies, while Wang *et al.* [24] considered spectrum optimization problem for cognitive satellite networks, and a spectrum allocation algorithm was proposed in [24] based on Bayesian equilibrium theory to achieve optimal spectrum sharing among SUs. Li *et al.* [25] considered the secure transmission for satellite links, and proposed a cooperative beamforming method to minimize the transmit power. A novel radio resource allocation algorithm based on multi-objective reinforcement learning was proposed in in [26]. In fact, authors in [18]–[26] only considered one dimensional resource allocation, and only few works concentrated on joint power and bandwidth optimization to further improve the system efficiency. Considering interference constrains and requirements of cognitive users, a joint power and timeslot allocation algorithm was designed in [27] to maximize the throughput of cognitive satellite networks. Lagunas *et al.* [28] divided the interference threshold of PUs into maximum power level of each SU, and presented a joint bandwidth allocation and power control scheme to improve total capacity. In [29], a joint power control and rate allocation algorithm was proposed to find fair solutions among cognitive users. However, the centralized resource resource management in [27]–[29] might increase the delay for the system and the blocking probability.

To the best of our knowledge, the resource allocation problem for cognitive satellite networks has not been well investigated. In this paper, we concentrate on the joint transmit power and bandwidth allocation problem for cognitive satellite uplinks, and consider constrains of interference, channel condition and quality of service (QoS) requirements of different users. Game theory has been applied to resource allocation problem, however, most of the game theory based resource allocation are non-cooperative ones [30]–[32]. The solution of non-cooperative games is not always optimal for the whole system, and the selfishness of each player may lead the game into bad ending like the well known Prisoner's dilemma. The cooperative game [15], [33]–[36] is a better choice to improve the system utility by cooperation of players. Different from existing resource allocation methods which only consider fairness or resource utilization, we introduce Nash bargaining game theory [35]–[37] to formulate a distributed resource allocation problem to balance fairness and the total capacity. The main contributions of the present paper are summarized as follows:

- We design a reasonable model of cognitive satellite network uplinks, where cognitive satellite users use the same frequency allocated to the terrestrial systems as PUs. The multi-beam technology and the multi-frequency time division multiple access (MF-TDMA) are introduced to enhance the frequency utilization and supply flexible bandwidth resource allocation framework. The aggregated interference model and interference threshold are used to protect the performance of primary microwave base stations.
- We propose a resource management architecture combining with centralized architecture and distributed one to improve the computational efficiency. The network control center (NCC) is deployed on board, and distributed computing units are used for cognitive satellite users and controllers of beams to calculate resource and updating resource states. NCC allocates resource based on the calculation of distributed computing units, which provides a proper trade-off between computational cost of NCC and the complexity of resource management.
- In order to control the interference to primary microwave base stations caused by cognitive satellite users and achieve a fair allocation with considerable total capacity, we detailedly investigate the joint transmit power and bandwidth allocation problem taking into account constrains of interference, receiving ability of satellite antenna, maximum transmit power of cognitive satellite users, channel condition and QoS requirements of different users. Based on game theory and proposed resource management architecture, we design the utility function for the allocation problem and formulate the problem as a cooperative bargaining game.
- The existence, uniqueness, and fairness of the solution to this game are proved analytically. and the near optimal

solution of the cooperative bargaining game is derived based on Lagrangian dual decomposition. To solve the problem, a efficient resource allocating algorithm is proposed based on subgradient method under the combined resource management architecture. Extensive simulations are given to analyze performance of proposed algorithm, which shows that proposed algorithm has proper convergence rate and solutions of proposed algorithm are Pareto-optimal and outperform some existing methods.

Through the simulation results, we analyze the performance of the proposed algorithm. The findings of this paper suggest: a) The proposed algorithm has a considerable convergence rate, and distributed computation can further improve computational efficiency; b) The multi-user and multi-beam diversity can improve total capacity, while interference constrains and the limitation of resource limits the performance boundary; c) Compared with existing methods, the proposed algorithm is Pareto optimal and can achieve a better trade-off between fairness among users and total capacity of the whole network.

The rest of paper is organized as follows. Section II describes the system model and problem formulation. In Section III, we design the resource allocation game based on Nash bargaining theory. The closed form solution for the Nash bargaining game and corresponding joint power and bandwidth allocation algorithm are derived and designed in Section IV. Numerical simulation results are provided in section V. We conclude our paper in Section VI.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. THE MODEL OF THE COGNITIVE SATELLITE NETWORK

We consider a multi-beam cognitive satellite network for uplinks, which is shown in Fig. 1. The multi-beam technology and MF-TDMA are adopted to enhance the frequency utilization and supply flexible bandwidth resource allocation framework [3]. The Geostationary orbit (GEO) satellite uses one global beam to supply control channel and L beams to improve capacity of multiple users with limited spectrum resource, where these users are overlaid on a primary terrestrial network. To reduce the system delay, the NCC is deployed on the satellite with the on-board processing payload. The main station is employed to collect state information from the satellite and upload control information via global beam. Total bandwidth of the network is denoted by B_{tot}, which is reused by users of each beam with frequency reuse factor α, hence, the bandwidth for each beam is $B_l = {B_{tot}}/{\alpha}$. With the application of MF-TDMA scheme, the bandwidth B_l is divided into F subchannels, and each subchannel has T timeslots for a frame. Each beam covers M satellite users, and these users reuse the same frequency band as SUs with a primary microwave base station for uplinks. The set of available resource blocks (timeslots) for the beam l can be denoted by

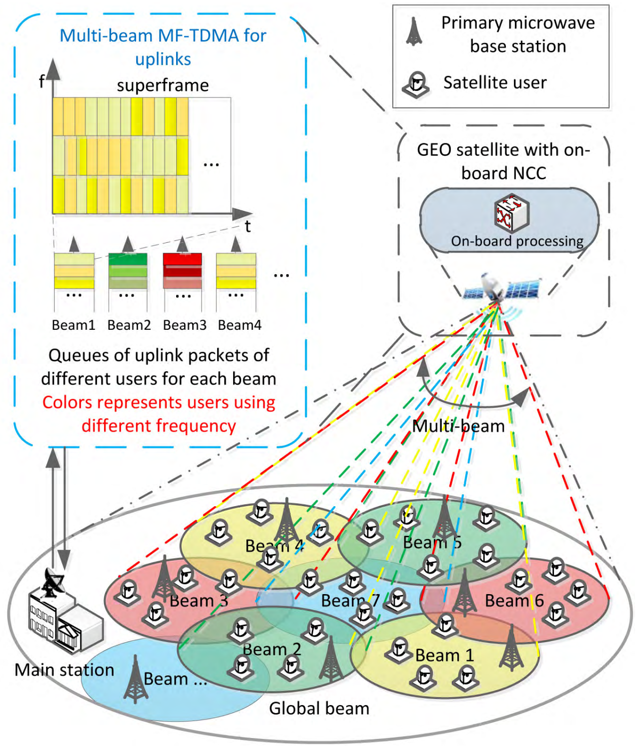

FIGURE 1. Cognitive satellite network.

$\boldsymbol{\omega}^l = \left\{\omega_{f,t}^l \,|f = 1, 2, \ldots, F,\ t = 1, 2, \ldots, T\right\}$, and we denote $\boldsymbol{\Delta} = \left[\delta_{l,m,f,t}\right]_{L\times M\times F\times T}$ as allcation matrix of resource blocks, where $\delta_{l,m,f,t} = 1$ and $\delta_{l,m,f,t} = 0$ represent that resource block $\omega_{f,t}^l$ is allocated to the user m under the beam l and $\omega_{f,t}^l$ is not assigned to this user, respectively. Denote $\mathbf{P} = \left[P_{l,m,f,t}\right]_{L\times M\times F\times T}$ as the allocation matrix of transmit power, where $P_{l,m,f,t}$ is the transmit power on the resource block $\omega_{f,t}^l$ for the user m under the beam l. Since the limitation of transmit power for PUs in terrestrial network, the interference from PUs to satellite can be ignored. We use $G_{l,m}^T$ and G_s^R to represent the gain of the transmitting antenna for user m under the beam l and the gain of the receiving antenna for the satellite, respectively. Denote $L_{l,m} = \left(\frac{4\pi d_{l,m} f}{c}\right)^2$ as the free space path loss, where c is the propagation speed and $d_{l,m}$ is the distance between the user m under the beam l and the satellite. We assume the users connected to the satellite directly, and the line of sight signal is the strongest signal, hence, the uplink channel between users and satellite can be modeled as a Rician fading channel with additive white Gaussian noise (AWGN) [38]. Denote $h_{l,m,f,t}$ as the channel fading coefficient on the resource block $\omega_{f,t}^l$ for user m under the beam l, the distribution of $\left|h_{l,m,f,t}\right|^2$ can be represented by the non-central chi-squares distribution probability density function as follow [38]

$$f_{|h_{l,m,f,t}|^2}(h) = \frac{1}{\sigma^2}\exp\left\{-\frac{s^2+h}{\sigma^2}\right\} I_0\left(2\sqrt{\frac{s^2 h}{\sigma^4}}\right), \quad (1)$$

where $s^2 = \mu_1^2 + \mu_2^2$ is the power of the LoS signal, σ^2 is the power of scattering signal, and $I_0(\bullet)$ is the first kind of zeroth order modified Bessel function.

With the channel model, the uplink-power-gain to noise ratio at the satellite receiving antenna of user m under the beam l can be expressed as

$$\gamma_{l,m,f,t} = \frac{G_{l,m}^T G_s^R \left|h_{l,m,f,t}\right|^2}{L_{l,m} N_0}, \tag{2}$$

where N_0 is the AWGN power. Letting SNR^{th} to denote the receiving signal to noise ratio (SNR) threshold of the satellite antenna, we have,

$$P_{l,m,f,t}\gamma_{l,m,f,t} \geq \delta_{l,m,f,t} SNR^{th}. \tag{3}$$

Based on Shannon's capacity formula [2], the achievable rate of user m under the beam l during one superframe can be defined as

$$R_{l,m} = \sum_{f=1}^{F}\sum_{t=1}^{T} \delta_{l,m,f,t} \log_2\left(1 + P_{l,m,f,t}\gamma_{l,m,f,t}\right). \tag{4}$$

As for primary microwave links, the uplinks of the cognitive satellite network using the same frequency cause interference to the microwave base stations. To protect the performance of the primary microwave system, the following interference constrain must be satisfied,

$$I_{l,f} \leq I_{l,f}^{th}, \quad l = 1, 2, \ldots, L,\ f = 1, 2, \ldots, F, \tag{5}$$

where $I_{l,f}^{th}$ denotes the tolerable interference threshold on subchannel f for the primary microwave base station under the beam l, and $I_{l,f}$ is the aggregated interference power on subchannel f caused by M satellite users under the beam l. The latter can be expressed as

$$I_{l,f} = \sum_{m=1}^{M}\sum_{t=1}^{T} \delta_{l,m,f,t} P_{l,m,f,t} g_{l,m,f,t}, \tag{6}$$

where $g_{l,m,f,t}$ denotes the channel gain from user m under the beam l to the primary microwave base station on the resource block $\omega_{f,t}^{l}$, which is given by

$$g_{l,m,f,t} = \frac{G_{l,m}^T G_l^R}{L_d L_s}, \tag{7}$$

where $L_s = \left(\frac{4\pi df}{c}\right)^2$ denotes free space path loss, d is the distance between cognitive satellite users and primary microwave base station, L_d is the diffraction loss, and G_l^R is the power gain of the receiving antenna for the primary microwave base station under the beam l [29].

B. RESOURCE MANAGEMENT ARCHITECTURE AND PROBLEM FORMULATION

In this paper, we consider the optimization of utilities for cognitive satellite users with protection of performance for primary microwave network. We only consider the resource allocation problem in this network, and the CR technologies for information sharing between PU and SU is assumed to be realized by some enabling technologies. We assumed that the primary microwave base stations can cooperate with satellite users, and the tolerable interference threshold $I_{l,f}^{th}$ and the channel gain $g_{l,m,f,t}$ can be broadcasted to satellite users by primary microwave base stations via dedicated channels. Different from existing works which adopt centralized resource management architecture [17], [23], [28], [29] or distributed resource management architecture [15], [16], we propose a combined resource management architecture to improve computational efficiency, which is shown in Fig. 2.

Under the architecture in Fig. 2, cognitive satellite users exchange information with microwave base station for cognitive access. The cognitive information can also be used for resource scheduling of the primary terrestrial network. The NCC is deployed on the satellite, and the main station of the cognitive satellite network is only responsible for maintaining the satellite and uploading the control information like updating code for the algorithm. The controllers of the NCC is divided into two parts: the central control unit and L beam-control units. The cognitive users collect local information of the resource state and deliver local information to beam-control units of the on-board NCC to obtain area information, and area information is delivered to the central control unit forming global resource state information. Since multi-beam MF-TDMA is adopted, the bandwidth resource can be allocated independently by each beam, and the distributed computing mechanism is introduced into the architecture with L beam-control units. The central control unit allocates the bandwidth resource based on a algorithm with global information, and the allocation solutions is fed back to beam-control units and cognitive users for resource configuration and calculation. Each cognitive satellite user calculates it's transmit power with local information and bandwidth allocation solutions, then, the local information is updated and sent back to the on-board NCC via global beam for next allocation. This architecture is combined with central resource management architecture and distributed one. Taking advantages of this two architecture, we can balance the conflicts between the computational costs of the NCC and the complexity of the network controlling.

Based on the cognitive satellite network model we built and the proposed resource management architecture, the resource allocation problem can be expressed as follows,

$$\max_{\mathbf{P},\Delta} f\left(\left[U_{l,m}\right]_{L\times M}\right), \tag{8}$$

$$\text{s.t.} \sum_{m=1}^{M}\sum_{t=1}^{T} \delta_{l,m,f,t} P_{l,m,f,t} g_{l,m,f,t} \leq I_{l,f}^{th}, \quad \forall l, f, \tag{9a}$$

$$P_{l,m,f,t}\gamma_{l,m,f,t} \geq \delta_{l,m,f,t} SNR^{th}, \ \forall l, m, f, t, \tag{9b}$$

$$0 \leq P_{l,m,f,t} \leq P_{l,m}^{\max}, \quad \forall l, m, f, t, \tag{9c}$$

$$\sum_{f=1}^{F} \delta_{l,m,f,t} \leq 1 \quad \forall l, m, t, \tag{9d}$$

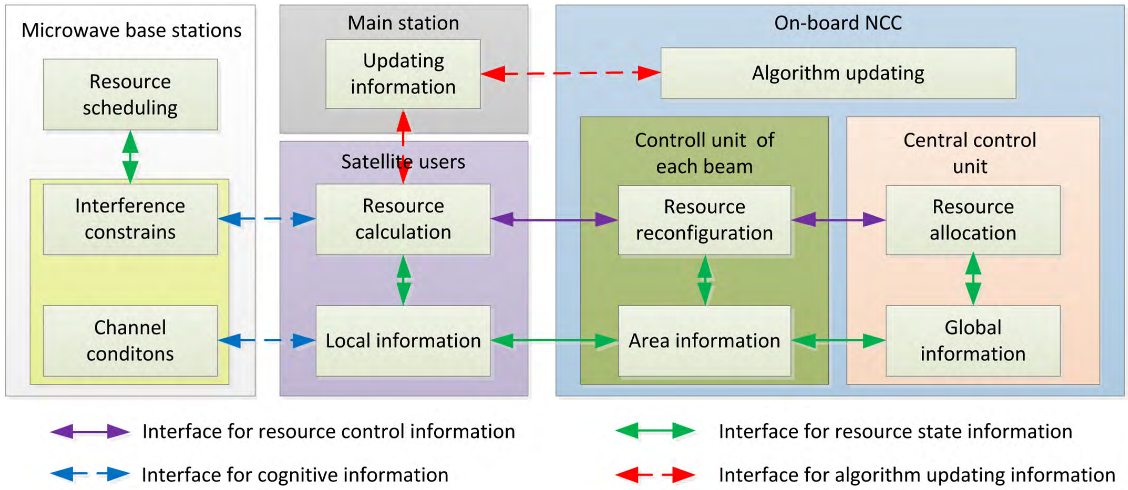

FIGURE 2. **Combined resource management architecture for cognitive satellite network.**

$$\sum_{m=1}^{M} \delta_{l,m,f,t} \leq 1 \quad \forall l, f, t, \tag{9e}$$

$$R_{l,m} \geq R_{l,m}^{\min}, \quad \forall l, m, \tag{9f}$$

where $U_{l,m}$ is the utility of the cognitive satellite user m the under beam l, and $f(\bullet)$ is the objective function. Eq. (9a) is the interference constrain for satellite users. Eq. (9b) is the constrain of SNR threshold for satellite receiving antenna. Eq. (9c) makes sure that the transmit power of each user is non-negative and limits the power below the maximum transmit power $P_{l,m}^{\max}$. Eq. (9d) represents that one satellite user can not occupy more than one subchannel during one timeslot. A resource block can only be allocated to one user, and this constrain is denoted by Eq. (9e). The constrains in Eq. (9f) is the QoS constrain, which ensures the achievable rate $R_{l,m}$ is higher than the required minimum data rate $R_{l,m}^{\min}$. The constrains in Eq. (9a)-(9f) are obtained by the exchanging of resource state information among satellite users, microwave base stations and on-board NCC. To improve the system efficiency and satisfy the constrains under the combined resource management architecture, we formulate the problem as bargaining game and design the $U_{l,m}$ and $f(\bullet)$ based on game theory in next section.

III. RESOURCE ALLOCATION BASED ON COOPERATIVE GAME

The interference constrain and the limitation of resource blocks lead to competition relationship among cognitive satellite users, and the resource allocation problem can be modeled as a game process based on game theory [30], [31]. Based on the assumption of information sharing among satellite users and the proposed resource management architecture, we model the resource allocation problem as a cooperative bargaining game [15]. In this section, the concepts and theory of bargaining game are reviewed briefly, and the utility function $U_{l,m}$ is designed based on the theory of bargaining game.

A. CONCEPTS OF BARGAINING GAME

The competition relationship caused by the interference constrain and resource limitation make the resource allocation to be a game process to obtain optimal utility of each cognitive satellite user. Based on game theory, games can be divided into two kinds of process: non-cooperative ones and cooperative ones. A non-cooperative game leads to a unique Nash equilibrium (NE), and players in this game are not motivated to cooperate and only care their own utilization [30]–[32]. With out cooperation, the NE is not always optimal for the whole system, and the selfishness of each player may lead the game into bad ending like the well known Prisoner's dilemma [35]. The cooperative game like Nash bargaining game can improve the system utility by cooperation of each player with shared information [36]. Based on the assumption of information sharing among satellite users and the proposed resource management architecture, we use a cooperative bargaining game to describe the resource allocation problem in this paper.

We assume there are K players participating in a Nash bargaining game, and let $U_k \in \mathbf{U}$ to be the utility of player k, where $\mathbf{U} = (\mathbf{U}_1, \ldots, \mathbf{U}_k, \ldots, \mathbf{U}_K)$ is nonempty, bounded, convex and closed space representing the feasible space of each user's utility [15]. Let $\mathbf{U}^{\min} = \left(U_1^{\min}, \ldots, U_k^{\min}, \ldots, U_K^{\min}\right)$ to be set of each user's minimum utility, and the solutions lower than the minimum utility will not accepted by players [36]. We can construct a Nash bargaining game $f\left(\mathbf{U}, \mathbf{U}^{\min}\right)$, and the optimal solution of $f\left(\mathbf{U}, \mathbf{U}^{\min}\right)$ is called Nash bargaining solution (NBS). The definition of the NBS is give by ***Definition*** 1 [15], [37].

Definition 1: $\mathbf{U}^* = \left(U_1^*, U_2^*, \ldots, U_K^*\right)$ is an NBS for the Nash bargaining game $f\left(\mathbf{U}, \mathbf{U}^{\min}\right)$, if $\mathbf{U}^*$ satisfied follow axioms.

1) *Individual rationality* ($U_k^* \geq U_k^{\min}$, $\forall k$);
2) *Feasibility* ($\mathbf{U}^* \in \mathbf{U}$);
3) *Pareto optimality* ($\mathbf{U}^*$ is Pareto optimal)

4) *Independence of irrelevant alternatives* (If $\mathbf{U}^* = \arg f\left(\mathbf{U}, \mathbf{U}^{\min}\right)$ and $\mathbf{U}^* \in \mathbf{U}' \subset \mathbf{U}$, then $\mathbf{U}^* = \arg f\left(\mathbf{U}', \mathbf{U}^{\min}\right)$);
5) *Independence of linear transformations* ($\xi\left(\mathbf{U}^*\right) = \arg f\left(\xi\left(\mathbf{U}\right), \xi\left(\mathbf{U}^{\min}\right)\right)$, where ξ represents any linear transformation);
6) *Symmetry* (If $\mathbf{U}$ is invariant under all exchanges of players, $U_i^* = U_j^*,\ \forall i, j$).

The axioms 1), 2) and 3) are the constrains of the NBS, which ensure the existence and optimality of $\mathbf{U}^*$. The axioms 4) and 5) guarantee the fairness of the Nash bargaining game. The axiom 6) ensures that if feasible space of all player are completely symmetric, then all players have the same priority, and the solutions of all players are the same [35]. Actually, there is a unique NBS that satisfies the axioms 1)-6), which is shown in Theorem 1 [36].

Theorem 1: If $\mathbf{U}$ is nonempty, bounded, convex and closed, there is a unique NBS $\mathbf{U}_{opt}$ for the Nash bargaining game $f\left(\mathbf{U}, \mathbf{U}^{\min}\right)$, and it can be denoted by

$$\mathbf{U}^{opt} = \arg \max_{U \in \mathbf{U}\ U \geq \mathbf{U}^{\min}} \prod_{k=1}^{K} \left(U_k - U_k^{\min}\right), \tag{10}$$

where $\mathbf{U}^{opt} = \left(U_1^{opt}, U_2^{opt}, \ldots, U_K^{opt}\right)$, and $U_k^{opt} \geq U_k^{\min},\ \forall k$.

Proof: The proof of ***Theorem*** 1 is omitted due to space limitations. A similar proof can be found in [40]. ■

With the concepts of the Nash bargaining game, we design the utility of resource allocation problem in Eq. (8), which is presented in next subsection.

B. COOPERATIVE RESOURCE ALLOCATION GAME

Based on the theory of bargaining game that we describe in previous subsection, the bargaining game model can be adopted to the proposed problem in this paper. Cognitive satellite users can be treated as $L \times M$ players in the bargaining game, and the resource allocation combinations are the strategies for players to choose to improve their utility. To obtain a fairness allocation with acceptable system utility, we define the utility of each satellite user $U_{l,m}$ as the achievable rate $R_{l,m}$, and feasible utility space $\mathbf{U}$ as the space constructed by the constrains in Eq. (9a)-(9e) (constrain in Eq. (9f) can be omitted since it is included in the Eq. (10)). Obviously, $\mathbf{U}$ for $U_{l,m}$ is nonempty, closed and bounded. Hence, we only need to proof $\mathbf{U}$ is convex, then, the problem can be formulated as a bargaining game [36].

Theorem 2: $\mathbf{U}$ is convex.

Proof: Based on the definition of convexity, $\mathbf{U}$ is convex if and only if $\theta \mathbf{U}\left(\mathbf{P}', \boldsymbol{\Delta}'\right) + (1-\theta)\,\mathbf{U}\left(\mathbf{P}'', \boldsymbol{\Delta}''\right) \in \mathbf{U}$ when $\mathbf{U}\left(\mathbf{P}', \boldsymbol{\Delta}'\right) \in \mathbf{U}$ and $\mathbf{U}\left(\mathbf{P}'', \boldsymbol{\Delta}''\right) \in \mathbf{U}$, where $0 \leq \theta \leq 1$. For constrain in Eq. (9a), only considering the resource blocks with $\delta_{l,m,f,t} = 1$ ($\delta_{l,m,f,t} = 0$ leads $\delta_{l,m,f,t} P_{l,m,f,t} g_{l,m,f,t} = 0$), we have

$$\sum_{m=1}^{M} \sum_{t=1}^{T} \theta P'_{l,m,f,t} g_{l,m,f,t} \leq \theta I_{l,f}^{th}, \tag{11}$$

$$\sum_{m=1}^{M} \sum_{t=1}^{T} (1-\theta)\, P''_{l,m,f,t} g_{l,m,f,t} \leq (1-\theta)\, I_{l,f}^{th}, \tag{12}$$

Letting Eq. (11) to plus Eq. (12), we have

$$\sum_{m=1}^{M} \sum_{t=1}^{T} \left(\theta P'_{l,m,f,t} + (1-\theta)\, P''_{l,m,f,t}\right) g_{l,m,f,t} \leq I_{l,f}^{th} \tag{13}$$

The constrains in Eq. (9b)-(9e) obviously satisfy the definition of convexity. Hence, $\mathbf{U}$ is convex. ■

Based on the concepts of bargaining game, the $U_{l,m}$ we designed can satisfy all the axioms in ***Definition*** 1. Besides, the NBS in Eq. (10) is equal to

$$\mathbf{U}^{opt} = \arg \max_{U \in \mathbf{U}\ U \geq \mathbf{U}^{\min}} \sum_{k=1}^{K} \ln\left(U_k - U_k^{\min}\right) \tag{14}$$

Hence, the resource allocation problem based on Nash bargaining game can be rewritten as follows

$$\max_{\mathbf{P}, \boldsymbol{\Delta}} \sum_{l=1}^{L} \sum_{m=1}^{M} \left(\ln\left(R_{l,m} - R_{l,m}^{\min}\right)\right), \tag{15}$$

$$s.t. \sum_{m=1}^{M} \sum_{t=1}^{T} \delta_{l,m,f,t} P_{l,m,f,t} g_{l,m,f,t} \leq I_{l,f}^{th}, \quad \forall l, f, \tag{16a}$$

$$P_{l,m,f,t} \gamma_{l,m,f,t} \geq \delta_{l,m,f,t} SNR^{th}, \quad \forall l, m, f, t, \tag{16b}$$

$$0 \leq P_{l,m,f,t} \leq P_{l,m}^{\max}, \quad \forall l, m, f, t, \tag{16c}$$

$$\sum_{f=1}^{F} \delta_{l,m,f,t} \leq 1 \quad \forall l, m, t, \tag{16d}$$

$$\sum_{m=1}^{M} \delta_{l,m,f,t} \leq 1 \quad \forall l, f, t, \tag{16e}$$

IV. SOLUTIONS OF COOPERATIVE RESOURCE ALLOCATION GAME

Based on the convex optimization theory, the convex optimal problem can be easily solved by transforming the original problem to it's dual problem. We prove the feasible utility space $\mathbf{U}$ is convex in previous section, we only need to prove the objective function $U_{l,m}$ is concave or convex.

Theorem 3: $U_{l,m}$ is concave.

Proof: Taking the first derivative of $\mathbf{U}$ with respect to $P_{l,m,f,t}$, we have

$$\frac{\partial U_{l,m}}{\partial P_{l,m,f,t}} = \sum_{f=1}^{F} \sum_{t=1}^{T} \frac{\delta_{l,m,f,t} \gamma_{l,m,f,t}}{\left(1 + P_{l,m,f,t} \gamma_{l,m,f,t}\right) \ln 2}. \tag{17}$$

For resource blocks allocated to satellite user m under the beam l, $\delta_{l,m,f,t} = 1$, otherwise, $\delta_{l,m,f,t} = 0$. To satisfy the QoS requirements, there are always some blocks

$$L(\mathbf{P}, \boldsymbol{\Delta}, \boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\beta}) = \sum_{l=1}^{L}\sum_{m=1}^{M}\left(\ln\left(\left(\sum_{f=1}^{F}\sum_{t=1}^{T}\delta_{l,m,f,t}\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)\right)-R_{l,m}^{\min}\right)\right)$$
$$+\sum_{l=1}^{L}\sum_{f=1}^{F}\lambda_{l,f}\left(I_{l,f}^{th}-\sum_{m=1}^{M}\sum_{t=1}^{T}\delta_{l,m,f,t}P_{l,m,f,t}g_{l,m,f,t}\right)$$
$$+\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\alpha_{l,m,f,t}\left(P_{l,m,f,t}\gamma_{l,m,f,t}-\delta_{l,m,f,t}SNR^{th}\right)$$
$$+\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\beta_{l,m,f,t}\left(P_{l,m}^{\max}-P_{l,m,f,t}\right) \tag{20}$$

that will be allocated to each satellite user, which means $\sum_{f=1}^{F}\sum_{t=1}^{T}\delta_{l,m,f,t}>0,\ \forall l,m$. Hence, we have

$$\sum_{f=1}^{F}\sum_{t=1}^{T}\frac{\delta_{l,m,f,t}\gamma_{l,m,f,t}}{\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)\ln 2}>0, \tag{18}$$

The second derivative of $\mathbf{U}$ with respect to $P_{l,m,f,t}$ is denoted by

$$\frac{\partial^2 U_{l,m}}{\partial P_{l,m,f,t}^2}=\sum_{f=1}^{F}\sum_{t=1}^{T}\frac{\delta_{l,m,f,t}\gamma_{l,m,f,t}^2}{\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)^2\ln 2}, \tag{19}$$

similar to Eq. (18)), we can obtain $\frac{\partial^2 U_{l,m}}{\partial P_{l,m,f,t}^2}>0$, hence, $U_{l,m}$ is concave. ■

Based on ***Theorem*** 3, the optimization problem in this paper is a convex optimal problem, which can be solved in it's dual domain with a iterative method.

A. DUAL PROBLEM AND SOLUTIONS

The solution gap between primal convex optimal problem and it's dual problem can be considered as 0 [34], hence, the optimization problem in this paper can be solved by minimizing it's dual problem. By introducing Lagrange multipliers $\{\lambda_{l,f}\}$, $\{\alpha_{l,m,f,t}\}$ and $\{\beta_{l,m,f,t}\}$, the Lagrangian function of the problem in this paper can be denoted by Eq. (20) as shown at the top of this page.

Thus, the dual function is denoted by

$$D(\boldsymbol{\lambda},\boldsymbol{\alpha},\boldsymbol{\beta})=\begin{cases}\max\limits_{\mathbf{P},\boldsymbol{\Delta}} L(\mathbf{P},\boldsymbol{\Delta},\boldsymbol{\lambda},\boldsymbol{\alpha},\boldsymbol{\beta})\\ s.t.\ \sum\limits_{f=1}^{F}\delta_{l,m,f,t}\le 1\quad \forall l,m,t\\ \qquad\sum\limits_{m=1}^{M}\delta_{l,m,f,t}\le 1\quad \forall l,f,t,\end{cases} \tag{21}$$

Hence, the problem in this paper can transfer into a dual problem, which can be expressed as

$$\min_{\boldsymbol{\lambda},\boldsymbol{\alpha},\boldsymbol{\beta}} D(\boldsymbol{\lambda},\boldsymbol{\alpha},\boldsymbol{\beta}). \tag{22}$$

Actually, the Lagrangian function can be rewritten as

$$L(\mathbf{P},\boldsymbol{\Delta},\boldsymbol{\lambda},\boldsymbol{\alpha},\boldsymbol{\beta})=L(\ldots)+\sum_{l=1}^{L}\sum_{f=1}^{F}\lambda_{l,f}I_{l,f}^{th}+\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\beta_{l,m,f,t}P_{l,m}^{\max}, \tag{23}$$

where $L(\ldots)$ is the component including $\delta_{l,m,f,t}$ and $P_{l,m,f,t}$, which is given by Eq. (24) shown at the top of the next page. Hence, we have

$$\max_{\mathbf{P},\boldsymbol{\Delta}} L(\mathbf{P},\boldsymbol{\Delta},\boldsymbol{\lambda},\boldsymbol{\alpha},\boldsymbol{\beta})\cong \max_{\mathbf{P},\boldsymbol{\Delta}} L(\ldots), \tag{25}$$

where $\max\limits_{\mathbf{P},\boldsymbol{\Delta}} L(\ldots)$ is denoted by Eq. (26) shown at the top of the next page. Problem in Eq. (26) can be decomposed into $L\times M$ subproblems, and each subproblems can be solved independently. With given $\{\lambda_{l,f}\}$, $\{\alpha_{l,m,f,t}\}$ and $\{\beta_{l,m,f,t}\}$, the first derivative of $L(\ldots)$ with respect to $P_{l,m,f,t}$ can be expressed as Eq. (27).

$$\frac{\partial L(\ldots)}{\partial P_{l,m,f,t}}=\frac{\frac{\delta_{l,m,f,t}\gamma_{l,m,f,t}}{(1+P_{l,m,f,t}\gamma_{l,m,f,t})\ln 2}}{\left(\delta_{l,m,f,t}\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)-R_{l,m}^{\min}\right)}-\lambda_{l,f}\delta_{l,m,f,t}g_{l,m,f,t}+\alpha_{l,m,f,t}\gamma_{l,m,f,t}-\beta_{l,m,f,t} \tag{27}$$

Leting $\Lambda\left(P_{l,m,f,t}\right)=1+P_{l,m,f,t}\gamma_{l,m,f,t}$ and $\phi=\lambda_{l,f}\delta_{l,m,f,t}g_{l,m,f,t}-\alpha_{l,m,f,t}\gamma_{l,m,f,t}+\beta_{l,m,f,t}$, we have

$$\frac{\partial L(\ldots)}{\partial P_{l,m,f,t}}=\frac{\frac{\delta_{l,m,f,t}\gamma_{l,m,f,t}}{\Lambda(P_{l,m,f,t})}}{\left(\delta_{l,m,f,t}\log_2\left(\Lambda\left(P_{l,m,f,t}\right)\right)-R_{l,m}^{\min}\right)\ln 2}-\phi. \tag{28}$$

Based on Karush-Kuhn-Tucher (KKT) conditions [15], leting $\frac{\partial L(\ldots)}{\partial P_{l,m,f,t}}=0$, we can obtain

$$\Lambda\left(P_{l,m,f,t}\right)\left(\log_2\left(\Lambda\left(P_{l,m,f,t}\right)\right)-\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}\right)=\frac{\gamma_{l,m,f,t}}{\phi\ln 2}. \tag{29}$$

$$L(\ldots) = \sum_{l=1}^{L}\sum_{m=1}^{M}\left(\ln\left(\left(\sum_{f=1}^{F}\sum_{t=1}^{T}\delta_{l,m,f,t}\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)\right)-R_{l,m}^{\min}\right)\right)$$
$$-\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\lambda_{l,f}\delta_{l,m,f,t}P_{l,m,f,t}g_{l,m,f,t}$$
$$+\sum_{l=1}^{L}\sum_{f=1}^{F}\sum_{m=1}^{M}\sum_{t=1}^{T}\alpha_{l,m,f,t}\left(P_{l,m,f,t}\gamma_{l,m,f,t}-\delta_{l,m,f,t}SNR^{th}\right)$$
$$-\sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\beta_{l,m,f,t}P_{l,m,f,t} \tag{24}$$

$$\max_{\mathbf{P},\boldsymbol{\Delta}} L(\ldots) = \max_{\mathbf{P},\boldsymbol{\Delta}}\sum_{l=1}^{L}\sum_{m=1}^{M}\left\{\begin{array}{l}\ln\left(\left(\sum_{f=1}^{F}\sum_{t=1}^{T}\delta_{l,m,f,t}\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)\right)-R_{l,m}^{\min}\right)\\ -\sum_{f=1}^{F}\sum_{t=1}^{T}\lambda_{l,f}\delta_{l,m,f,t}P_{l,m,f,t}g_{l,m,f,t}\\ +\sum_{m=1}^{M}\sum_{t=1}^{T}\alpha_{l,m,f,t}\left(P_{l,m,f,t}\gamma_{l,m,f,t}-\delta_{l,m,f,t}SNR^{th}\right)\\ -\sum_{f=1}^{F}\sum_{t=1}^{T}\beta_{l,m,f,t}P_{l,m,f,t}\end{array}\right\} \tag{26}$$

Eq. (29) can be rewritten as

$$\frac{\Lambda\left(P_{l,m,f,t}\right)}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}}\log_2\left(\frac{\Lambda\left(P_{l,m,f,t}\right)}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}}\right)=\frac{\gamma_{l,m,f,t}}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}\phi\ln 2}. \tag{30}$$

Leting $\zeta = \frac{\Lambda(P_{l,m,f,t})}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}}$, we have

$$\zeta^{\zeta} = 2^{\frac{\gamma_{l,m,f,t}}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}\phi\ln 2}}. \tag{31}$$

Based on Lambert-W function, ζ is give by

$$\zeta = \exp\left(W\left(\ln\left(2^{\frac{\gamma_{l,m,f,t}}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}\phi\ln 2}}\right)\right)\right). \tag{32}$$

where $W(\bullet) = \sum_{i=1}^{+\infty}\left({(-i)^{i-1}}/{i!}\right)(\bullet)^i$ is the Lambert-W function [15]. Substituting $\Lambda\left(P_{l,m,f,t}\right) = 1 + P_{l,m,f,t}\gamma_{l,m,f,t}$, $\phi = \lambda_{l,f}\delta_{l,m,f,t}g_{l,m,f,t} - \alpha_{l,m,f,t}\gamma_{l,m,f,t} + \beta_{l,m,f,t}$ and $\zeta = \frac{\Lambda(P_{l,m,f,t})}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}}$ into Eq. (32), we can obtain Eq. (33) shown at the top of the next page. Hence, with given optimal resource block allocation solution $\hat{\delta}_{l,m,f,t}$, the optimal power allocation solution can be denoted by Eq. (34), which is shown at the top of the next page, where $(x)^+ = \max(0, x)$.

With given the optimal power allocation $\hat{P}_{l,m,f,t}$, the first derivative of $L(\ldots)$ with respect to $P_{l,m,f,t}$ can be expressed as Eq. (35).

$$\frac{\partial L(\ldots)}{\partial\delta_{l,m,f,t}} = \frac{\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)}{\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)-R_{l,m}^{\min}} - \lambda_{l,f}P_{l,m,f,t}g_{l,m,f,t} - \alpha_{l,m,f,t}SNR^{th} \tag{35}$$

Letting

$$T\left(P_{l,m,f,t}\right) = \frac{\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)}{\log_2\left(1+P_{l,m,f,t}\gamma_{l,m,f,t}\right)-R_{l,m}^{\min}} - \lambda_{l,f}P_{l,m,f,t}g_{l,m,f,t},$$

we have $\frac{\partial L(\ldots)}{\partial\delta_{l,m,f,t}} = T\left(P_{l,m,f,t}\right) - \alpha_{l,m,f,t}SNR^{th}$. If we consider $\delta_{l,m,f,t}$ as continuous variable in [0, 1], to maximize the objective function, user whose utility has fastest increase of $\delta_{l,m,f,t}$ will occupy the bandwidth resource. Hence, the resource block $\omega_{f,t}^{l}$ will be allocated to the user who has the maximum $T\left(P_{l,m,f,t}\right)$ with the given optimal power allocation $\hat{P}_{l,m,f,t}$ [17], which can be denoted as

$$\hat{\delta}_{l,m,f,t} = \begin{cases}1\ (l,m) = \arg\max T\left(\hat{P}_{l,m,f,t}\right), & \forall f,t\\ 0\ (l,m) \neq \arg\max T\left(\hat{P}_{l,m,f,t}\right), & \forall f,t\end{cases} \tag{36}$$

$$\frac{1+P_{l,m,f,t}\gamma_{l,m,f,t}}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}} = \exp\left(W\left(\ln\left(2^{\frac{\gamma_{l,m,f,t}}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}\left(\lambda_{l,f}\delta_{l,m,f,t}g_{l,m,f,t}-\alpha_{l,m,f,t}\gamma_{l,m,f,t}+\beta_{l,m,f,t}\right)\ln 2}}\right)\right)\right) \quad (33)$$

$$\hat{P}_{l,m,f,t} = \frac{1}{\gamma_{l,m,f,t}}\left(2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}\exp\left(W\left(\ln\left(2^{\frac{\gamma_{l,m,f,t}}{2^{\frac{R_{l,m}^{\min}}{\delta_{l,m,f,t}}}\left(\lambda_{l,f}\delta_{l,m,f,t}g_{l,m,f,t}-\alpha_{l,m,f,t}\gamma_{l,m,f,t}+\beta_{l,m,f,t}\right)\ln 2}}\right)\right)\right)-1\right)^{+} \quad (34)$$

B. UPDATE OF THE LAGRANGE MULTIPLIERS

The analytical solutions of $P_{l,m,f,t}$ and $\delta_{l,m,f,t}$ obtained in Eq. (34) and Eq. (36) are functions with respect to Lagrange multipliers $\{\lambda_{l,f}\}$, $\{\alpha_{l,m,f,t}\}$ and $\{\beta_{l,m,f,t}\}$. To obtain the optimal solution, we need to solve the dual optimal problem to find the best Lagrange multipliers. The subgradient method is considered in this paper for updating the Lagrange multipliers. Based on subgradient method, we have ***Lemma*** 1.

Lemma 1: The subgradients of the Lagrange multipliers $\{\lambda_{l,f}\}$, $\{\alpha_{l,m,f,t}\}$ and $\{\beta_{l,m,f,t}\}$ is denoted as follows.

$$\Delta\lambda_{l,f} = I_{l,f}^{th} - \sum_{m=1}^{M}\sum_{t=1}^{T}\delta_{l,m,f,t}P_{l,m,f,t}g_{l,m,f,t}, \quad (37)$$

$$\Delta\alpha_{l,m,f,t} = P_{l,m,f,t}\gamma_{l,m,f,t} - \delta_{l,m,f,t}SNR^{th}, \quad (38)$$

$$\Delta\beta_{l,m,f,t} = P_{l,m}^{\max} - P_{l,m,f,t}, \quad (39)$$

where $\Delta\lambda_{l,f}$, $\Delta\alpha_{l,m,f,t}$ and $\Delta\beta_{l,m,f,t}$ are the subgradients of $\{\lambda_{l,f}\}$, $\{\alpha_{l,m,f,t}\}$ and $\{\beta_{l,m,f,t}\}$, respectively.

Proof: Based on the definition of the dual function in Eq. (21), we have

$$D\left(\boldsymbol{\lambda}',\boldsymbol{\alpha}',\boldsymbol{\beta}'\right) = \max_{\mathbf{P},\boldsymbol{\Delta}} L\left(\mathbf{P},\boldsymbol{\Delta},\boldsymbol{\lambda}',\boldsymbol{\alpha}',\boldsymbol{\beta}'\right), \quad (40)$$

where $\{\boldsymbol{\lambda}',\boldsymbol{\alpha}',\boldsymbol{\beta}'\}$ is the new multipliers with respect to $\{\boldsymbol{\lambda},\boldsymbol{\alpha},\boldsymbol{\beta}\}$, the solution $\hat{\mathbf{P}}$ and $\hat{\boldsymbol{\Delta}}$ is not optimal for $D\left(\boldsymbol{\lambda}',\boldsymbol{\alpha}',\boldsymbol{\beta}'\right)$, thus, we have

$$D\left(\boldsymbol{\lambda}',\boldsymbol{\alpha}',\boldsymbol{\beta}'\right) \geq L\left(\hat{\mathbf{P}},\hat{\boldsymbol{\Delta}},\boldsymbol{\lambda}',\boldsymbol{\alpha}',\boldsymbol{\beta}'\right). \quad (41)$$

Meanwhile, $L\left(\hat{\mathbf{P}},\hat{\boldsymbol{\Delta}},\boldsymbol{\lambda}',\boldsymbol{\alpha}',\boldsymbol{\beta}'\right)$ can be rewritten as Eq. (42) shown at the top of the next page. Taking the maximum of both side of Eq. (42), we can obtain Eq. (43) at the top of the next page. Eq. (43) verifies the definition of subgradient and completes the proof. ∎

With subgradients in ***Lemma*** 1, we can update the Lagrange multipliers with following equations.

$$\lambda_{l,f}^{(i+1)} = \left(\lambda_{l,f}^{(i)} - \theta_{\lambda}^{(i)}\Delta\lambda_{l,f}\right), \quad (44)$$

$$\alpha_{l,m,f,t}^{(i+1)} = \left(\alpha_{l,m,f,t}^{(i)} - \theta_{\alpha}^{(i)}\Delta\alpha_{l,m,f,t}\right), \quad (45)$$

$$\beta_{l,m,f,t}^{(i+1)} = \left(\beta_{l,m,f,t}^{(i)} - \theta_{\beta}^{(i)}\Delta\beta_{l,m,f,t}\right), \quad (46)$$

where $\theta_j^{(i)}$ for $j=\lambda,\alpha,\beta$ is the step length of iteration i, and it must satisfy following condition,

$$\sum_{i=1}^{\infty}\theta_j^{(i)} = \infty, \quad \lim_{i\to\infty}\theta_j^{(i)} = 0. \quad (47)$$

Combining Eq. (44)-(46) with Eq. (34) and Eq. (36), we can solve the resource allocation problem based on bargaining game. We design an iteration algorithm to find the NBS under the combined resource management architecture that we proposed in this paper, which is described in next subsection.

C. COOPERATIVE RESOURCE ALLOCATION ALGORITHM

The subgradient method can be realized by an iteration algorithm. Let $I_{\max}$ to be the maximum time of iterations, and ε_j for $j=\lambda,\alpha,\beta$ to be the terminating index for each Lagrange multiplier. The terminating conditions are denoted by

$$\lambda_{l,f}^{(i)}\Delta\lambda_{l,f} \leq \varepsilon_{\lambda}, \quad (48)$$

$$\alpha_{l,m,f,t}^{(i)}\Delta\alpha_{l,m,f,t} \leq \varepsilon_{\alpha}. \quad (49)$$

$$\beta_{l,m,f,t}^{(i)}\Delta\beta_{l,m,f,t} \leq \varepsilon_{\beta}. \quad (50)$$

We design an iteration algorithm called cooperative resource allocation algorithm for the power allocation and bandwidth scheduling problem in cognitive satellite networks, which is shown in Algorithm 1. We assume that satellite users can share information with microwave base station via free channel, and the channel conditions and interference threshold are known by the satellite users before allocation. At the beginning of the algorithm, on-board NCC initializes parameters of the cooperative resource allocation game, and broadcasts relevant parameters to cognitive satellite users. $\mathbf{P}$ is initialized with an uniform distribution among resource blocks. $\boldsymbol{\Delta}$ is initialized by Eq. (36) with the initial power. In each iteration, cognitive satellite users and the on-board NCC are cooperative based on the bargaining game theory with the proposed combined resource management architecture. To reduce computation costs of the on-board NCC, the calculation of the $\hat{P}_{l,m,f,t}$ and $\boldsymbol{\beta}$ is realized by distributed computation of cognitive satellite users. Since the calculation of $\hat{\delta}_{l,m,f,t}$ and the updating of $\boldsymbol{\lambda}$ need the power allocation solutions of each beam, this part of computation is in charged by central control units of on-board NCC. $\boldsymbol{\alpha}$ is also updated by on-board NCC, because $\hat{\delta}_{l,m,f,t}$ is needed for the updating.

$$
\begin{aligned}
L\left(\hat{\mathbf{P}}, \hat{\boldsymbol{\Delta}}, \boldsymbol{\lambda}', \boldsymbol{\alpha}', \boldsymbol{\beta}'\right) = & \sum_{l=1}^{L}\sum_{f=1}^{F}\left(\lambda'_{l,f} - \lambda_{l,f}\right)\left(I_{l,f}^{th} - \sum_{m=1}^{M}\sum_{t=1}^{T}\hat{\delta}_{l,m,f,t}\hat{P}_{l,m,f,t}g_{l,m,f,t}\right) \\
& + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\left(\alpha'_{l,m,f,t} - \alpha_{l,m,f,t}\right)\left(\hat{P}_{l,m,f,t}\gamma_{l,m,f,t} - \hat{\delta}_{l,m,f,t}SNR^{th}\right) \\
& + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\left(\beta'_{l,m,f,t} - \beta_{l,m,f,t}\right)\left(P_{l,m}^{\max} - \hat{P}_{l,m,f,t}\right) + L\left(\hat{\mathbf{P}}, \hat{\boldsymbol{\Delta}}, \boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\beta}\right)
\end{aligned} \tag{42}
$$

$$
\begin{aligned}
D\left(\boldsymbol{\lambda}', \boldsymbol{\alpha}', \boldsymbol{\beta}'\right) \geq & \sum_{l=1}^{L}\sum_{f=1}^{F}\left(\lambda'_{l,f} - \lambda_{l,f}\right)\left(I_{l,f}^{th} - \sum_{m=1}^{M}\sum_{t=1}^{T}\hat{\delta}_{l,m,f,t}\hat{P}_{l,m,f,t}g_{l,m,f,t}\right) \\
& + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\left(\alpha'_{l,m,f,t} - \alpha_{l,m,f,t}\right)\left(\hat{P}_{l,m,f,t}\gamma_{l,m,f,t} - \hat{\delta}_{l,m,f,t}SNR^{th}\right) \\
& + \sum_{l=1}^{L}\sum_{m=1}^{M}\sum_{f=1}^{F}\sum_{t=1}^{T}\left(\beta'_{l,m,f,t} - \beta_{l,m,f,t}\right)\left(P_{l,m}^{\max} - \hat{P}_{l,m,f,t}\right) + D\left(\boldsymbol{\lambda}, \boldsymbol{\alpha}, \boldsymbol{\beta}\right)
\end{aligned} \tag{43}
$$

Algorithm 1 Cooperative Resource Allocation Algorithm for Cognitive Satellite Networks

Require: $I_{\max}$, ε_j
Ensure: $\mathbf{P}$, $\boldsymbol{\Delta}$
On-board NCC initializes $I_{\max}$, $\mathbf{P}$, $\boldsymbol{\Delta}$, $\boldsymbol{\lambda}$, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$;
On-board NCC broadcasts $\mathbf{P}$, $\boldsymbol{\Delta}$, $\boldsymbol{\lambda}$, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ to cognitive satellite users via global beam;
repeat
  for $l = 1$ to L **do**
    for $m = 1$ to M **do**
      for $f = 1$ to F **do**
        for $t = 1$ to T **do**
          Cognitive satellite users calculate $\hat{P}_{l,m,f,t}$ based on Eq. (34), and send it back to on-board NCC via global beam;
          On-board NCC calculates $\hat{\delta}_{l,m,f,t}$ based on Eq. (36);
          On-board NCC updates $\boldsymbol{\lambda}$ and $\boldsymbol{\alpha}$ based on Eq. (44) and Eq. (44), respectively;
          Cognitive satellite users update $\boldsymbol{\beta}$ based on Eq. (46), $i = i + 1$;
        end for
      end for
    end for
  end for
  On-board NCC broadcasts $\hat{\delta}_{l,m,f,t}$, $\boldsymbol{\lambda}$ and $\boldsymbol{\alpha}$ to satellite via global beam;
  Cognitive satellite users send $\boldsymbol{\beta}$ back to satellite via global beam;
until Meet the terminating condition in Eq. (48)-(50) or $i = I_{\max}$

The distributed computation is adopted by on-board NCC with L independent beam-control units.

In this algorithm, the cognitive satellite users under each beam cooperate with each other to obtain the cognitive accessing power based on local information, and on-board NCC collects global information of the networks and allocates the bandwidth to users. Distributed computation can improve efficiency, and the the propagation delay caused by the information exchanging can be ignored since the exchanging process can be operated with calculation and updating simultaneously. Without complex operators, the algorithm can be easily applied to engineering practice.

V. SIMULATION RESULTS

In this section, we give simulation results related to the performance of the proposed cooperative resource allocation algorithm. The simulation parameters of the cognitive satellite network is presented in Table 1. We consider a cognitive satellite network adopted multi-beam MF-TDMA. Under different simulation scenes, the number of beams changed from 15 to 50, and each beam covers 10 to 50 cognitive satellite users to access the same spectrum ($30GHz$) resource with the terrestrial network. The total bandwidth for the cognitive satellite uplinks is 100 MHz, and the bandwidth reuse factor among different beams α is 4, hence, the available bandwidth B_l for each beam is 25 MHz. Based on the characteristic of MF-TDMA, B_l is divided into 30 subchannels, and each subchannels provided 20 timeslots for each frame (allocation period). The distance between the GEO satellite and satellite users is set as 36000 Km, and the distance between satellite users and microwave base station is a random number from 0.5 to 2 Km. The maximum transmitting power of each satellite user is 50 dBm, and three interference thresholds

TABLE 1. Parameter Table for Cognitive Satellite Network.

Parameters	Values
Number of beams L	15 to 50
Users under each beam M	10 to 40
Frequency	30 GHz
Total bandwidth B	100 MHz
Bandwidth reuse factor α	4
Number of subchannels F	30
Number of timeslots T	20
$d_{l,m}$	36000 Km
d	0.5 to 2 Km
Maximum power of users $P_{l,m}^{\max}$	50 dBm
Interference threshold $I_{l,f}^{th}$	-90, -100, -110 dBm
s^2/σ^2	7 dB
$s^2+\sigma^2$	8 dB
Diffraction loss L_d	2 dB
Noise power N_0	-150 dBm
Transmitting gain $G_{l,m}^T$	45 dB
Receiving gain of satellite G_s^R	50 dB
Receiving gain of base station G_s^R	45 dB

TABLE 2. Parameter Table for Proposed Algorithm.

Parameters	Values
Maximum iteration I_max	100
Terminating index ε_j	0.001

(-90, -100 and -110 dBm) are considered as the power constrain. The channel fading is assumed as a non-central chi-squared distributed random variable, which is obtained by eq. (1) with $s^2/\sigma^2 = 7\,dB$ and $s^2+\sigma^2 = 8\,dB$. The diffraction loss for the channel between cognitive satellite users and microwave base stations is 2 dB, and the noise power is -150 dB. The transmitting gain of each cognitive satellite user, the receiving gain of satellite and receiving gain of each microwave base station are 45, 50, 45 dB, respectively. Table 2 shows the parameters of the proposed algorithm, which presents the maximum iteration I_{max} and terminating index ε_j to ensure the convergence of Algorithm 1.

The simulation results are divided into two parts: the performance of the proposed algorithm and the comparison with existing methods. To research the performance of the algorithm, the convergence of the algorithm is provided with different interference constrains, and the total capacities of the cognitive satellite network under different conditions are compared. The comparison between the proposed algorithm and existing methods shows the effectiveness of our algorithm.

A. PERFORMANCE OF PROPOSED ALGORITHM

First of all, we investigate the convergence of the proposed algorithm with three different interference thresholds (-90, -100 and -110 dBm), and the results are shown in Fig. 3. The number of beam L and the cognitive users under each beam M are 15 and 10, respectively. The minimum rate requirement of each cognitive user $R_{l,m}^{min}$ is 0.5 bps/Hz. As we can see from Fig. 3, the total uplink capacity of cognitive

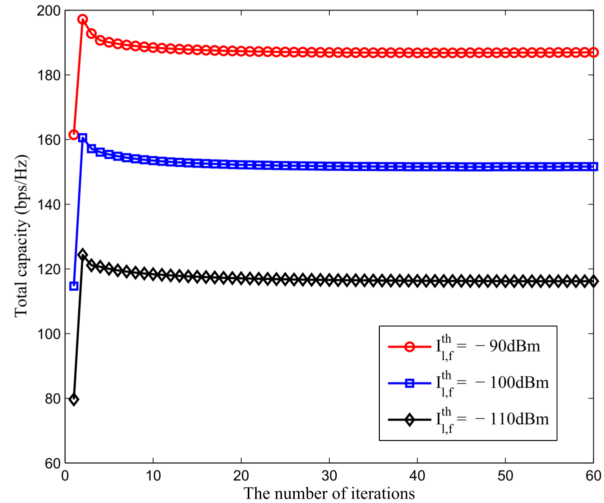

FIGURE 3. Convergence of the proposed algorithm.

satellite network reaches it's optimal value after no more than 40 iterations for different interference constrains, which indicates the proper convergence rate of the proposed algorithm. Besides, the optimal total capacity increases with the increase of the interference threshold, because of the power competition among cognitive users.

Fig. 4 shows the total uplink capacity of cognitive satellite network with the number of beams increasing from 15 to 50. The number of cognitive satellite users under each beam M is 10. The minimum rate requirement of each cognitive user $R_{l,m}^{min}$ is 0.5 bps/Hz. The channel state information (CSI) is considered, and the real channel gain to noise ratio $\gamma_{l,m,f,t}^{*}$ can be denoted by

$$\gamma_{l,m,f,t}^{*} = \hat{\gamma}_{l,m,f,t} + \Delta\gamma_{l,m,f,t}, \tag{51}$$

where $\hat{\gamma}_{l,m,f,t}$ is the estimation of the channel gain to noise ratio, and $\Delta\gamma_{l,m,f,t}$ is the channel estimation error, which can be modeled as a zero-mean complex Gaussian random variable. The actual rate of cognitive satellite users is calculated with $\gamma_{l,m,f,t}^{*}$. The variance of the zero-mean complex Gaussian distribution is set as 0.06. The receiving SNR at satellite antenna for some users with negative channel estimation errors might be lower than the threshold SNR^{th}, and the actual rate of these users is considered as 0. In Fig. 4, the solid lines show the total capacity of the network with perfect CSI, and the dash lines represent the actual total capacity of the network with imperfect CSI. Similar to Fig. 3, the optimal total capacity increases with the increase of the interference threshold. The actual total capacity with imperfect CSI is lower than the total capacity with perfect CSI for any number of beams, because of the channel estimation error $\Delta\gamma_{l,m,f,t}$. Hence, a proper resource reserving method should be adopted for networks with imperfect CSI. The total capacity increases with the increase of the number of beams, because of the multi-beam diversity and the frequency reuse.

The total capacity of the network with cognitive satellite user under each beam increasing from 10 to 40 is shown

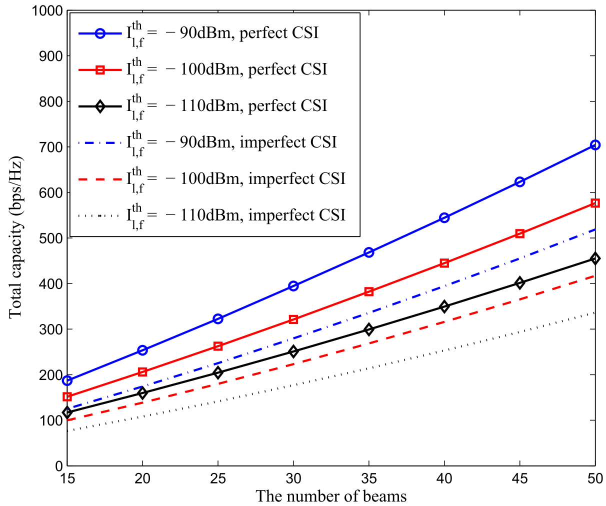

FIGURE 4. **Total capacity of the network vs number of beams.**

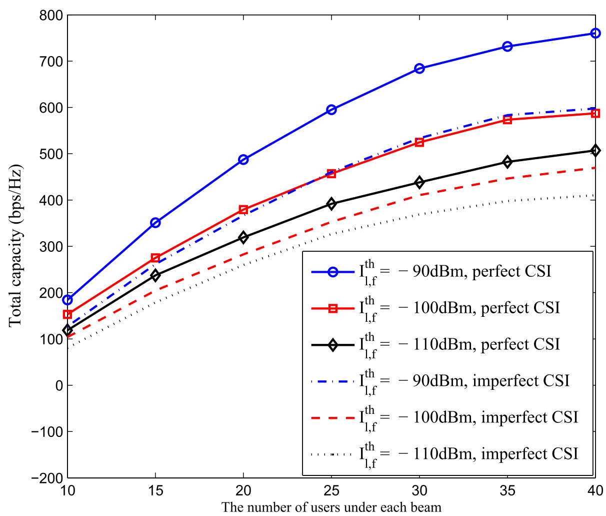

FIGURE 5. **Total capacity of the network vs number of users.**

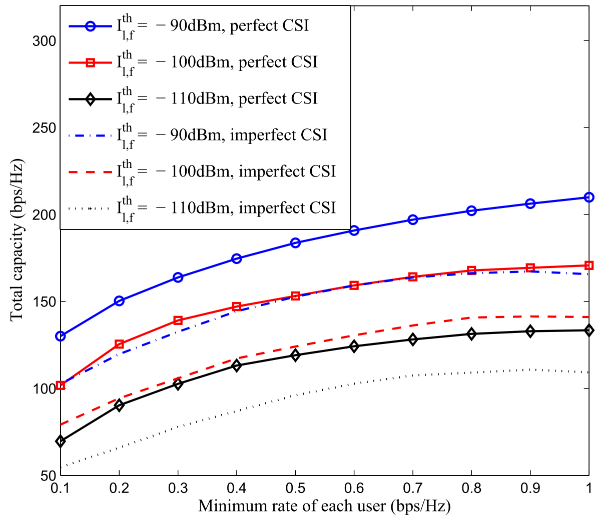

FIGURE 6. **Convergence time of TDICA, improved ICA, GA and NSGA-II.**

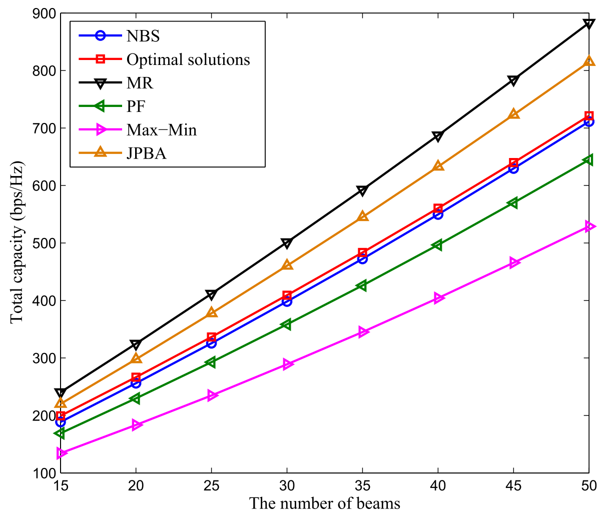

FIGURE 7. **Total capacity of the network for different methods.**

in Fig. 5. The number of beams L is 15. The minimum rate requirement of each cognitive user $R^{min}_{l,m}$ is 0.5 bps/Hz. The imperfect CSI is modeled as same as Fig. 4. Similar to Fig. 3 and Fig. 4, the optimal total capacity increases with the increase of the interference threshold, and the total capacity with perfect CSI is higher than the actual total capacity with imperfect CSI. The total capacity increases with the increase of the number of cognitive satellite users, because of the multi-user diversity. The total capacity grows more and more slowly with the increase of the number of cognitive satellite users, because of power competition among cognitive satellite users and limitation of the bandwidth resource.

Fig. 6 shows the total capacity of the network under different QoS requirements. The QoS requirement is represented by the minimum rate requirement $R^{min}_{l,m}$, which is changed from 0.1 to 1 bps/Hz. The number of beams L is 15, and the number of cognitive satellite users under each beam M is 10. Similar to Fig. 3, Fig. 4 and Fig. 5, the optimal total capacity increases with the increase of the interference threshold, and the total capacity with perfect CSI is higher than the actual total capacity with imperfect CSI. The total capacity increases with the increase of minimum rate requirement, because of higher $R^{min}_{l,m}$ expands the range of the feasible space of the solutions. The total capacity grows more and more slowly with the increase of $R^{min}_{l,m}$, because of interference constrains, power constrains and limitation of bandwidth resource.

B. COMPARISON WITH EXISTING METHODS

Through previous analysis, we prove the proposed algorithm has proper convergence rate, and the total capacity of the network under different simulating conditions is investigate to support the theoretical analysis in this paper. To show the effectiveness of the proposed algorithm, we compare some representative indexes with existing methods.

Fig. 7 shows the total capacity of the network for different methods with the number of beams increasing from 15 to 50. The number of cognitive satellite users under each beam M is 10. The minimum rate requirement of each cognitive user $R_{l,m}^{min}$ is 0.5 bps/Hz. The interference threshold of the microwave base stations is -90 dBm. We compare the total capacity of the network with four representative methods: maximum rate (MR) allocation in [23], proportion fairness (PF) allocation in [28], and max-min fairness allocation in [28] and the joint power and bandwidth allocation (JPBA) in [29]. By dividing interference threshold of the microwave base station into maximum interference levels for cognitive satellite users, the JPBA method calculates the maximum transmit power and allocate the bandwidth based on MR objective function. To investigate the gap between the NBS of the dual problem and the optimal solutions of the original problem in Eq. (15), we compare the performance of the optimal solutions of the original problem with NBS, and the optimal solutions are obtained by exhaustive search method. As we can see from Fig. 7, The total capacity of MR method and the JPBA method are better than the proposed method, while the performance of max-min method and the PF method are lower than the NBS. The gap between the NBS and the optimal solutions of Eq. (15) is very close, which proves the accuracy and effectiveness of the proposed algorithm since the high complexity of the exhaustive search.

The NBS is a fair allocation to balance the system utilization and the users utility. Fig. 8 shows the fairness index of different methods under the same simulation conditions of Fig. 7. The fairness index [41] is denoted by

$$Fi = \frac{\left(\sum_{l=1}^{L}\sum_{m=1}^{M}\left(\frac{R_{l,m}}{R_{l,m}^{\min}}\right)\right)^2}{\left(LM\left(\sum_{l=1}^{L}\sum_{m=1}^{M}\left(\frac{R_{l,m}}{R_{l,m}^{\min}}\right)^2\right)\right)}. \tag{52}$$

As we can see from Fig. 8, PF method and max-min method perform better than NBS with the fairness index in Eq. (52), while the fairness index of MR method and JPBA method are lower than NBS. Analyzing along with the results in Fig. 7, we can find that the proposed algorithm can obtain a proper trade-off between total capacity and fairness among cognitive satellite users.

To analyze the Pareto optimality of the proposed algorithm, we investigate the competition relationship between two group of users with different minimum rate requirement, and the results are shown in Fig. 9. The number of beams L is 15. The number of users in group 1 and group 2 under each beam are both 5, and the minimum rate requirement of group 1 and group 2 are 0.25 bps/Hz and 0.5 bps/Hz, respectively. The interference threshold of the microwave base stations is -90 dBm. Similar to Fig. 7, the gap between Pareto front of the dual problem in Eq. (22) and the original problem in Eq. (15) is very close, where the Pareto front is the set of all feasible Pareto optimal solutions. As we can see from Fig. 9, solutions of MR method, NBS of the proposed method, solutions of PF and max-min method all lie in the Pareto front, which means these methods are Pareto optimal. Solutions of JPBA method is not Pareto-optimal, because of the assumption of maximum

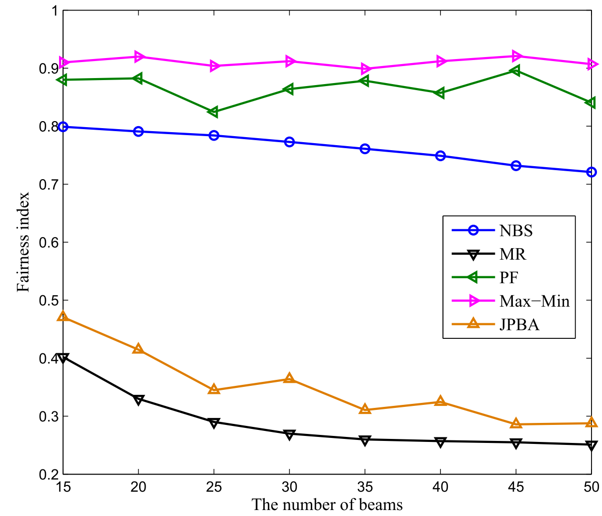

FIGURE 8. Fairness index of the network for different methods.

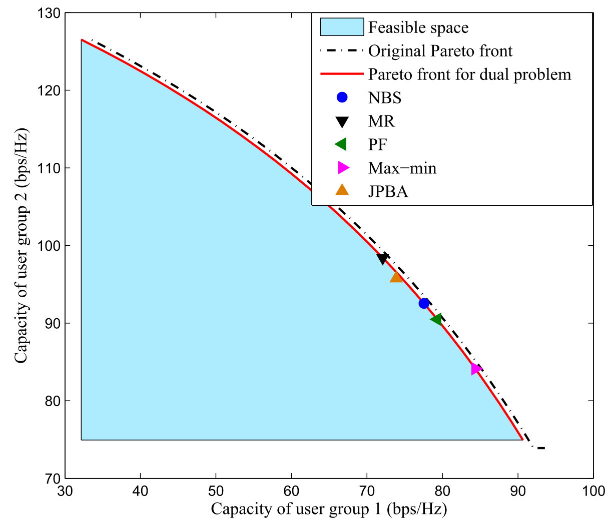

FIGURE 9. Pareto optimality of different methods.

interference levels for each cognitive satellite user. The MR method obtained maximum sum-rate with unacceptable fairness among users. The max-min method give the same rate between two group of users, which causes large system performance loss. The PF method achieves better performance by allocating the rates to users with difference based on channel conditions, however, the total capacity of the network for PF methods is relatively low compared with MR method. The proposed method improved total capacity with acceptable fairness loss compared with PF method, which proves the feasibility and high efficiency of the proposed algorithm.

VI. CONCLUSION

In this papaer, the characteristics of the cognitive satellite uplins has been described and analyzed, based on this, a reasonable model cognitive satellite networks has been designed, and a combined resource management architecture is proposed to improve efficiency of resource allocation.

Considering interference constrains resource limitation, QoS requirements, channel conditions, transmission capability of satellite users and receiving capability of satellite, a joint resource allocation problem has been formulated based on Nash bargaining theory to obtain fair allocation with acceptable total capacity of the network. After the existence, uniqueness, and fairness of the solution to the allocation game and the convexity of the problem have been proved, a iteration algorithm has been proposed to solve the problem in it's dual domain.

With numerical simulation results, the performance of the proposed algorithm has been analyzed. The proposed algorithm has a considerable convergence rate under differen simulation conditions, and distributed computation can further improve computational efficiency. The multi-user and multi-beam diversity can improve total capacity, while interference constrains and the limitation of resource limits the performance boundary. Compared with existing methods, the proposed algorithm is Pareto optimal and can achieve a better trade-off between fairness among users and total capacity of the whole network.

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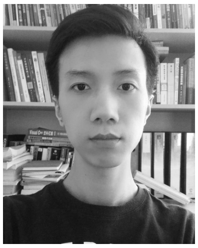

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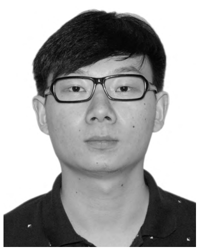

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