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LA GESTION DES RESSOURCES RADIO DANS LES SYSTÈMES SATELLITAIRES

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Résumé

0.1 Motivations et Contributions

En raison de la croissance constante du trafic satellitaire, de plus en plus de satellites ont été lancés sur l'orbite. Cela conduit à une congestion croissante à la fois sur l'orbite terrestre et le spectre radioélectrique, ce qui entraîne une augmentation de l'interférence radioélectrique dans les communications par satellites. De plus, la réutilisation du spectre pour les communications dans différents faisceaux de satellites à faisceaux multiples, qui génère des interférences co-canal, peut entraîner une dégradation de la fiabilité et des performances de la communication si les interférences ne sont pas gérées de manière appropriée. Pour lutter contre l'atténuation des interférences et mieux exploiter les ressources de la radio par satellite, nous avons proposé des techniques avancées d'allocation des ressources pour les communications satellitaires. Plus précisément, nous avons mis au point des cadres de gestion des ressources radioélectriques dans le système à satellite unique et le système à deux satellites coexistants.

Pour le système à satellites multi-faisceaux, nous avons étudié le problème en traivaillant sur la formation de faisceaux, de l'allocation des porteuses et de l'allocation des utilisateurs, qui vise à maximiser la somme des taux du système et la somme des utilités . Pour résoudre les deux problèmes sous-jacents, deux algorithmes itératifs d'allocation de ressources correspondantes ont été développés. Dans les deux algorithmes, nous avons utilisé la méthode de formation de faisceaux appelée l'erreur quadratique moyenne pondérée avancée (WMMSE) pour déterminer les formateurs de faisceaux sur la base desquels l'affectation de porteuse et la conception d'ordonnancement d'utilisateur peuvent être adressées. Des résultats numériques étendus ont démontré l'efficacité et la performance souhaitable des algorithmes proposés.

Pour le système à deux satellites coexistants, nous avons développé un cadre d'allocation de ressource de liaison inverse à base radio cognitive, dans lequel les deux satellites ont été traités respectivement comme un satellite primaire et secondaire. La conception de l'affectation des ressources pour ce paramètre implique l'optimisation de l'allocation de puissance et des angles d'antenne des utilisateurs afin de maximiser la somme des taux moyens du système en considérant les contraintes maximales de puissance et de protection contre les interférences. Pour réaliser cette conception, nous avons dérivé la solution d'allocation de puissance optimale pour des angles d'utilisateurs secondaires donnés et dérivé les angles d'utilisateurs secondaires optimaux pour une solution d'allocation de puissance donnée. Ensuite, nous avons proposé un algorithme itératif

d'allocation des ressources basées sur ces dérivations pour résoudre le problème considéré. Enfin, nous avons effectué des études numériques pour étudier la performance de l'algorithme proposé qui ont confirmé la supériorité de performance de l'algorithme proposé par rapport à d'autres approches classiques d'allocation de ressources.

0.2 Allocation des Ressources pour les MISO Satellites à Faisceaux Multiples

Cette section aborde les deux problèmes d'allocation de ressources qui visent à maximiser la somme des taux du système et la somme des utilités de tous les utilisateurs dans le système de satellite multi-faisceau. Nous présentons deux algorithmes d'allocation de ressources différents pour résoudre les problèmes considérés.

0.2.1 Modèle du Système et Formulation du Problème

Nous considérons la liaison descendante d'un système satellitaire à faisceaux multiples où le nombre d'antennes est J et qu'il y a une seule alimentation d'antenne par faisceau. Le satellite est censé être équipé d'antennes J et chaque utilisateur a une seule antenne. Notre problème est d'optimiser l'attribution du faisceau d'émission et de la sélection d'ensembles utilisateur pour chaque porteuse de sorte que les objectifs de conception sous-jacents sont maximisés.

Nous désignons P_{tot} comme la puissance totale du satellite, N comme le nombre de porteuses, J comme le nombre de faisceaux. De plus, nous supposons qu'il y a K utilisateurs à antenne unique dans le système, et nous indiquons S_j comme l'ensemble des utilisateurs dans le faisceau j. Le symbole de données transmis à l'utilisateur i est noté s_i où la puissance moyenne de s_i est donnée par $\mathbb{E}(s_i^2) = 1$ et son vecteur de formation de faisceau est $\mathbf{w}_{i,n}$. Soit $\mathbf{h}_{i,n}$ le gain de canal du satellite à l'utilisateur i sur la porteuse n. De plus, nous introduisons des variables d'optimisation binaire pour capturer les décisions d'ordonnancement de l'utilisateur où $a_{i,n}$ est égal à 1 si l'utilisateur i est desservi par le satellite sur la porteuse n, et qu'il est 0, sinon. Le signal reçu au rapport interférences plus bruit (SINR) de l'utilisateur i sur la porteuse n peut être exprimé comme

$$\Gamma_{i,n} = \frac{a_{i,n}|\mathbf{h}_{i,n}\mathbf{w}_{i,n}|^2}{\sum_{k\neq i} a_{k,n}|\mathbf{h}_{i,n}\mathbf{w}_{k,n}|^2 + \sigma^2}, \tag{1}$$

où σ^2 indique la puissance du bruit.

Ensuite, la somme des taux du système est donné par

$$R = \sum_{i=1}^{K}\sum_{n=1}^{N} \log_2(1 + \Gamma_{i,n}), \tag{2}$$

qui est le taux total atteint par tous les utilisateurs.

Nous étudions ensuite deux problèmes d'optimisation: le problème de la somme des taux maximale (MSRP) et le problème d'utilité maximale (MUP), qui sont présentés ci-dessous.

0.2.1.1 Problème de la Somme des Taux Maximale (MSRP)

Le problème du MSRP peut être écrit comme

$$\underset{\{a_{i,n}\},\{\mathbf{w}_{i,n}\}}{\text{maximiser}} \quad R \tag{3}$$

$$\text{sujet à} \quad \sum_{i=1}^{K}\sum_{n=1}^{N} a_{i,n}\mathbf{w}_{i,n}^{H}\mathbf{w}_{i,n} \leqslant P_{tot}, \tag{4}$$

où (4) capture la contrainte sur la puissance maximale du satellite.

0.2.1.2 Problème d'utilité Maximale (MUP)

Le problème du MUP peut être formulé comme

$$\underset{\{a_{i,n}\},\{\mathbf{w}_{i,n}\}}{\text{maximiser}} \quad u_{\mathsf{tot}} \tag{5}$$

$$\text{sujet à} \quad \sum_{i=1}^{K}\sum_{n=1}^{N} a_{i,n}\mathbf{w}_{i,n}^{H}\mathbf{w}_{i,n} \leqslant P_{tot}, \tag{6}$$

où la somme des utilités u_{tot} est donnée comme

$$u_{\mathsf{tot}} = \sum_{i=1}^{K} u_i(\overline{R}_i) = \sum_{i=1}^{K} \log_2(\overline{R}_i). \tag{7}$$

Ici, $\overline{R}_i$ est le taux moyen à long terme de l'utilisateur i, qui est mis à jour dans chaque intervalle de temps comme

$$\overline{R}_i(t+1) = \alpha\overline{R}_i(t) + (1-\alpha)R_i(t+1), \tag{8}$$

où $0 < \alpha < 1$ est une constante et $R_i(t)$ indique le taux de l'utilisateur i à l'heure t.

0.2.2 Algorithmes d'allocation des Ressources

Dans cette section, nous présentons les algorithmes d'allocation de ressources proposés et nous évaluons leur performance.

0.2.2.1 Algorithme de Formation de Faisceaux MMSE

La formation de faisceau est conçue pour chaque porteuse qui est affectée au groupe d'utilisateurs correspondant (c'est-à-dire, déterminée à partir des variables $a_{i,n}$). Pour la brièveté, nous ignorons les notations n et $a_{i,n}$ dans la conception du faisceau. Pour une sélection d'un ensemble d'utilisateurs donnée pour une porteuse considérée, les problèmes d'allocation de ressources peuvent être exprimés sous la forme générale suivante:

$$\underset{\{\mathbf{w}_i\}}{\text{maximiser}} \quad f(\mathbf{w}) \tag{9}$$

$$\text{sujet à} \quad \sum_{i\in S} \mathbf{w}_i^{H}\mathbf{w}_i \leqslant P_{tot}, \tag{10}$$

où la fonction $f(.)$ correspond à la fonction $R(.)$ et $u_{\mathsf{tot}}(.)$ dans les deux problèmes considérés, respectivement et cette optimisation est effectuée pour l'ensemble des utilisateurs programmés S sur la porteuse n.

Nous effectuons une répartition uniforme de puissance sur les porteuses; par conséquent, la puissance maximale allouée par porteuse est P_{tot}/N. Nous pouvons résoudre le problème (9) - (10) en résolvant le problème de minimisation de l'erreur quadratique moyenne (MSE) suivant [1]

$$\underset{\{\beta_i\},\{U_i\},\{\mathbf{w}_i\}}{\text{minimiser}} \quad \sum_{i\in S}\{\beta_i^c E_i + c_i\left(\gamma_i\left(\beta_i\right)\right) - \beta_i^c\left(\gamma_i\left(\beta_i\right)\right)\} \tag{11}$$

$$\text{sujet à} \quad \sum_{i\in S}\mathbf{w}_i^H\mathbf{w}_i \leqslant \frac{P_{tot}}{N}, \tag{12}$$

où E_i est la MSE, qui est définie comme

$$E_i = \mathbb{E}\left\{\left(\hat{r_i} - r_i\right)\left(\hat{r_i} - r_i\right)^c\right\}, \tag{13}$$

où $\mathbb{E}$ indique l'espérance, $\hat{r_i} = U_i^c r_i$ et U_i indique le poids de détection du récepteur (RX); $(X)^c$ désigne le conjugué de x. De plus, γ_i est le mappage inverse de la carte de gradient $\nabla c_i\left(E_i\right)$ et β_i est un paramètre de poids; $c_i(E_i)$ est la fonction de coût définie comme $c_i(E_i) = -u_i\left(-\log_2(E_i)\right)$. Notons que pour le problème de la maximisation de la somme des taux, nous avons $u_i = R_i$.

Pour résoudre le problème (11), nous corrigeons deux des trois ensembles de variables $\{\beta_i\}$, $\{U_i\}$, $\{\mathbf{w}_i\}$ et calculons la troisième. Les mises à jour itératives suivantes sont utilisées pour calculer ces variables. Nous mettons à jour le paramètre de poids RX U_i en utilisant le récepteur MMSE

$$U_i = \left(\sum_{l\in S}\mathbf{h}_i\mathbf{w}_l\mathbf{w}_l^H\mathbf{h}_i^H + \sigma^2\right)^{-1}\mathbf{h}_i\mathbf{w}_i, \forall i \in S. \tag{14}$$

Le paramètre de poids β_i est mis à jour en utilisant la condition d'optimalité du premier ordre pour β_i comme suit:

Pour le problème de la somme des taux maximale:

$$\beta_i = \left(1 - U_i^c\mathbf{h}_i\mathbf{w}_i\right)^{-1}, \forall i \in S. \tag{15}$$

Pour le problème d'utilité maximale:

$$\beta_i = \frac{\left(1-\alpha\right)E_i^{-1}}{\left(\alpha\bar{R}_i + \left(1-\alpha\right)\log_2(E_i^{-1})\right)}, \forall i \in S. \tag{16}$$

De plus, nous mettons à jour le formateur de faisceau d'émission $\mathbf{w}_i$ à partir de la condition d'optimalité du premier ordre comme suit:

$$\mathbf{w}_i = \left(\sum_{l\in S}\mathbf{h}_l^H U_l\beta_l U_l^c\mathbf{h}_l + \mu_i^*\mathbf{I}\right)^{-1}\mathbf{h}_i^H U_i\beta_i, \forall i \in S, \tag{17}$$

où $\mu_i^* \geq 0$ est le multiplicateur de Lagrange, qui peut être calculé comme décrit dans [1], et $\mathbf{I}$ est la matrice identité. L'algorithme de formation de faisceau WMMSE est résumé dans l'algorithme 1.

Compte tenu de cette conception du faisceau, nous développerons la stratégie d'ordonnancement et les algorithmes globaux pour résoudre le MSRP et le MUP dans les sections suivantes.

Algorithm 1 Algorithme de Formation de Faisceaux MMSE

Entrée: Le formateur de faisceau d'émission de choix initial $\mathbf{w}_i$'s tel que $\mathsf{Tr}\{\mathbf{w}_i\mathbf{w}_i^H\} = \frac{P_{tot}}{N.J}$.

Sortie: Le formateur de faisceau d'émission $\mathbf{w}_i$'s.
Initialiser: $\mathbf{w}_i$'s
while 1 **do**
  Mettre à jour : $\beta_i^{'} = \beta_i$.
  Calculer: $U_i = \left(\sum_{l\in S}\mathbf{h}_i\mathbf{w}_l\mathbf{w}_l^H\mathbf{h}_i^H + \sigma^2\right)^{-1}\mathbf{h}_i\mathbf{w}_i, \forall i \in S$.
  Calculer: $\beta_i = \left(1 - U_i^c\mathbf{h}_i\mathbf{w}_i\right)^{-1}, \forall i \in S$ pour MSRP
  et $\beta_i = \frac{(1-\alpha)E_i^{-1}}{\left(\alpha\bar{R}_i+(1-\alpha)\log_2(E_i^{-1})\right)}, \forall i \in S$ pour MUP.
  Calculer: $\mathbf{w}_i = \left(\sum_{l\in S}\mathbf{h}_l^H U_l\beta_l U_l^c\mathbf{h}_l + \mu_i^*\mathbf{I}\right)^{-1}\mathbf{h}_i^H U_i\beta_i$, $\forall i \in S$.
  if: $\mid \sum_{i\in S}\log(\beta_i) - \sum_{i\in S}\log\left(\beta_i^{'}\right) \mid < \epsilon$.
  break.
  end
end while

0.2.2.2 Algorithme de la Somme des Taux Maximale (MSRA)

Avec la conception de faisceaux WMMSE présentée, nous pouvons calculer la solution de formation de faisceau et par conséquent, nous déduisons les taux correspondants obtenus par les utilisateurs prévus sur la même porteuse. Sur la base de cette observation, nous développons un algorithme avide d'ordonnancement de l'utilisateur pour chaque porteuse (nous ignorons l'indice de porteuse pour la brièveté) où nous choisissons séquentiellement le «meilleur» utilisateur à ajouter au jeu de planification sur les itérations.

Pour plus d'explication de l'algorithme, soient $i_1, i_2, i_3, \ldots$ désignant l'utilisateur choisi dans la première, deuxième et troisième itération. Par ailleurs, soit $R_{i_1}, \forall i_1 = 1, .., K$, le taux obtenu par l'utilisateur i_1. Ensuite, le «meilleur» utilisateur i_1^* dans la première itération est celui qui atteint le taux maximal, c'est-à-dire,

$$i_1^* = \underset{i_1}{\operatorname{argmax}}\{R_{i_1}\}. \tag{18}$$

Avec l'utilisateur choisi i_1^*, qui est supposé appartenir au faisceau j_1, nous ajoutons un utilisateur de plus i_2, $i_2 \in \{1, .., J\}\backslash\{J_1\}$ dans l'un des faisceaux restants pour former le sous-ensemble

$\{i_1^*, i_2\}$ (nous planifions un seul utilisateur par faisceau sur chaque porteuse pour éviter de fortes interférences). Notez que nous pouvons calculer la somme des taux du système avec deux utilisateurs après avoir exécuté l'algorithme de formation de faisceau WMMSE présenté, désigné par $R_{i_1^*, i_2}$. Nous choisissons le second utilisateur i_2^*, qui appartient au faisceau j_2, comme suit:

$$i_2^* = \underset{i_2}{\operatorname{argmax}}\{R_{i_1^*, i_2}\}. \tag{19}$$

Ensuite, avec l'ensemble $\{i_1^*, i_2^*\}$, nous ajoutons un utilisateur i_3, $i_3 \in \{1, .., J\} \backslash \{j_1, j_2\}$ dans un des faisceaux restants pour former le sous-ensemble $\{i_1^*, i_2^*, i_3\}$ sur la base du taux cumulé obtenu $R_{i_1^*, i_2^*, i_3}$ similairement

$$i_3^* = \underset{i_3}{\operatorname{argmax}}\{R_{i_1^*, i_2^*, i_3}\}. \tag{20}$$

Nous pouvons poursuivre ce processus pour rechercher et ajouter les utilisateurs 4-ème, 5-ème ... jusqu'à ce que nous trouvions un utilisateur pour chaque faisceau. Cet algorithme est décrit dans Algorithme 2.

Algorithm 2 Algorithme de la Somme des Taux Maximale (MSRA)

1: **Entrée:** Taille du groupe $G = 1$, gains des canaux satellites
2: **Sortie:** Ensemble planifié d'utilisateurs pour chaque porteuse et formateur de faisceau
3: **Initialiser:** Taille du groupe $G = 1$
4: **while** $G \leqslant J$ **do**
5: **Trouver :** L'utilisateur i_G^* qui satisfait

$$i_G^* = \underset{i_G}{\operatorname{argmax}}\{R_{i_1^*, i_2^* .., i_G}\}, \forall i_G \in J \backslash \{j_1, j_2, .., j_{G-1}\}, \tag{21}$$

où $R_{i_1^*, i_2^* .., i_G}$ est la somme des taux du système pour l'utilisateur fixé $i_1^*, i_2^* .., i_G$ calculé en utilisant **Algorithme 1**.
6: **Mettre à jour:** $G = G + 1$.
7: **end while**

0.2.2.3 Algorithme d'utilité Maximale (MUA)

Nous proposons un algorithme itératif, appelé Algorithme utilité maximale (MUA), où nous effectuons les tâches suivantes de formation de faisceaux et de planification en deux étapes comme suit.

1. **Étape 1:** Les formateurs de faisceaux sont trouvés en résolvant le problème d'utilité maximale pour un programme prévu utilisateur fixé sur chaque porteuse n (donnée $a_{i,n}$ obtenue dans l'itération précédente) comme suit:

$$\underset{\{\mathbf{w}_{i,n}\}}{\text{maximiser}} \quad u_{\mathsf{tot}} \tag{22}$$

$$\text{sujet à} \quad \sum_{i \in S} a_{i,n} \mathbf{w}_{i,n}^H \mathbf{w}_{i,n} \leqslant \frac{P_{tot}}{N}, \tag{23}$$

où l'utilisateur programmé pour la porteuse sous-jacente n est $S \subset \{1, .., K\}$ où $a_{i,n} = 1$ si $i \in S$. Nous appliquons ensuite l'algorithme de formateur de faisceau WMMSE pour déterminer les vecteurs de formation de faisceaux $\mathbf{w}_{i,n}$.

2. **Étape 2:** Nous supposons que dans chaque faisceau et chaque porteuse, il y aura un utilisateur desservi par le satellite. Par conséquent, le nombre de faisceaux pour chaque porteuse est égal au nombre de faisceaux.

   Avec le formateur de faisceaux conçu à l'étape 1, pour le b-ème vecteur formateur de faisceau $b = \{1, .., J\}$, nous trouvons l'utilisateur i^*, $i^* \in S_j$, à programmer dans le faisceau $j \in \{1, ..., K\}$ comme suit:

$$a_{i^*,n} = 1 \Leftrightarrow i^* = \underset{i \in S_j}{\operatorname{argmax}} \{ \frac{\tilde{R}_{ib}}{\overline{R}_i} \}, \tag{24}$$

   où $\tilde{R}_{ib}$ est le taux obtenu par l'utilisateur i quand il est servi par formateur de faisceau b et le taux moyen $\overline{R}_i$ est mis à jour comme dans (8).

Cette stratégie proposée est résumée en Algorithme 3.

Algorithm 3 Algorithme d'utilité Maximale (MUA)

Entrée: Choix initial des utilisateurs programmés, nombre maximum d'itérations T_{max}, gain des canaux satellites
Sortie: Ensemble planifié d'utilisateurs pour chaque porteuse et formateur de faisceaux
Initialiser: Itération $t = 1$, les utilisateurs initiaux programmés sont choisis au hasard.
while $t < T_{\mathsf{max}}$ **do**
  Calculer: formateurs de faisceaux en utilisant **Algorithme 1**
  Pour chaque formateur de faisceau de chaque faisceau, trouver: utilisateur i^* qui satisfait

$$i^* = \underset{i \in S_j}{\operatorname{argmax}} \{ \frac{\tilde{R}_{ib}}{\overline{R}_i} \}. \tag{25}$$

  Mettre à jour: Utilisateur choisi pour la porteuse considérée et taux moyens $\overline{R}_i$.
  Mettre à jour: $t = t + 1$.
end while

0.2.3 Résultats Numériques

Pour la simulation, nous considérons un système satellitaire à trois faisceaux et deux utilisateurs par faisceau. Les paramètres de système utilisés dans les simulations sont résumés dans le Tableau 1 , sauf indication contraire. Nous adoptons le modèle de canal satellite dans [2]. Pour le problème MSRP, l'ensemble initial d'utilisateurs est choisi au hasard tandis que les valeurs initiales des formateurs de faisceaux dans l'algorithme WMMSE (Algorithme 1) sont définies selon les formateurs de faisceaux Zero-Forcing (ZF) où le nombre d'utilisateurs pour chaque porteuse est inférieur ou égal au nombre de faisceaux. De plus, la puissance de l'utilisateur est égale à la puissance totale (par porteuse) divisée par le nombre d'utilisateurs lorsque le nombre d'utilisateurs est plus grand que le nombre de faisceaux.

Table 1: Paramètres du système de simulation (liaison descendante)

Paramètres	Valeur
Orbite	GEO
Nombre de faisceaux	3
Nombre des porteuses	5
Nombre d'utilisateurs par faisceau	2
Diamètre du faisceau	250km
Angle $3dB$	0.4^o
Moyenne d'atténuation de la pluie	-2.6dB
Variance d'atténuation de la pluie	1.63dB
FL perte d'espace libre	210dB
Variance du bruit	$\sigma^2 = 10^{-24}$
α	0.9

Dans Fig. 1, nous montrons la somme des taux du système par rapport à la puissance du satellite en raison de la MSRA proposée. Pour obtenir ces résultats, nous choisissons 10 choix aléatoires différents d'ensembles initialement planifiés d'utilisateurs et montrons la valeur moyenne du débit de données à travers différentes simulations s'exécute. Nous montrons également les résultats obtenus à partir de la recherche exhaustive des meilleurs ensembles d'utilisateurs programmés pour le MSRP à des fins d'analyse comparative. Nous pouvons voir que la somme des taux due à notre MSRA proposé est très proche de celui dû à la recherche exhaustive, ce qui confirme l'efficacité de notre algorithme. Notez que notre MSRA proposé est basé sur le mécanisme d'ordonnancement avide donc il a beaucoup moins de complexité que celui dû à la recherche exhaustive. En outre, cette figure illustre la somme des taux de MUA est beaucoup plus faible que celui dû à MSRA. C'est le prix en terme de somme système que l'on doit payer pour plus équitable dans le partage des ressources pour les utilisateurs, comme nous le verrons plus loin.

Dans Fig. 2, nous montrons les débits de données des différents utilisateurs en raison des algorithmes MSRA et MUA proposés et les indices d'équité correspondants des deux algorithmes où la puissance du satellite est de 50W. Nous pouvons voir que le MUA se traduit par une répartition plus juste des taux pour différents utilisateurs par rapport à la MSRA. Ceci est

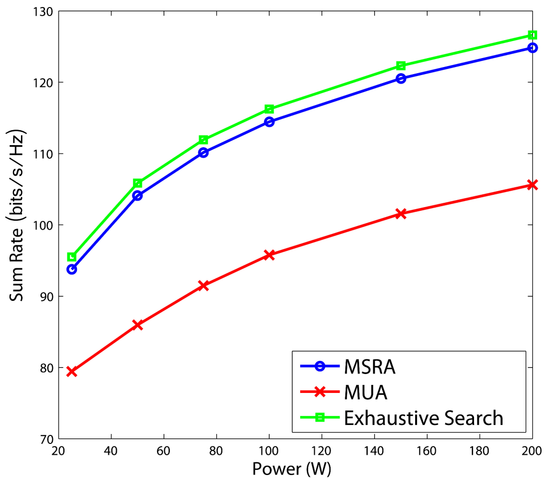

Figure 1: La somme des taux du système par rapport à la puissance des satellites

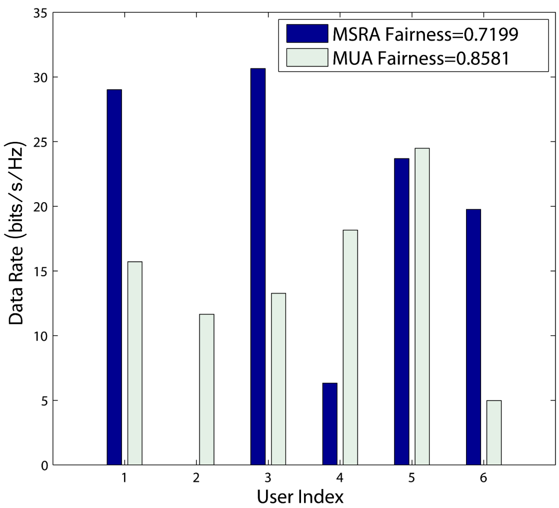

Figure 2: Répartition des tarifs des utilisateurs

également confirmé par le fait que l'indice d'équité de MUA est plus élevé que celle de MSRA (0.8581 contre 0.7199, respectivement).

0.3 Allocation de Ressources Basée sur la Radio Cognitive en Deux Satellites

Dans cette section, nous présentons la conception de l'affectation des ressources pour les communications de liaison montante des deux satellites fonctionnant sur le même spectre en utilisant le concept radio cognitive. La conception vise à maximiser la somme des taux moyens soumis à des contraintes des puissances maximales et l'interférence moyenne au niveau du satellite primaire.

0.3.1 Modèle du Système et Formulation du Problème

Nous considérons les communications en amont de deux satellites avec zones de service et bandes de fréquences se chevauchant où l'on est considéré comme le satellite primaire et l'autre est le satellite secondaire. Nous supposons qu'il y a des utilisateurs de satellite à antenne unique secondaire de K et qu'ils partagent des porteuses de fréquence autorisées de N avec le satellite primaire sous contraintes d'interférence à préciser prochainement. Dans cette section, nous étudions l'allocation de ressources pour les utilisateurs de satellites secondaires seulement. En outre, nous supposons que chaque porteuse peut être allouée au plus un utilisateur de satellite, mais un utilisateur de satellite peut utiliser de multiples porteuses.

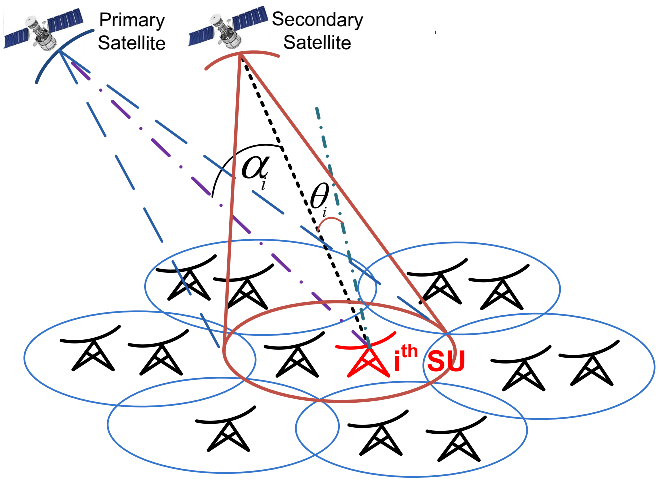

Figure 3: Système à Deux Satellites

Soit C_i l'ensemble des porteuses attribuées à l'utilisateur de satellite $i^{\text{ème}}$ et $p_{i,n}$ désignent la puissance d'émission de $i^{\text{ème}}$ utilisateur du satellite sur la porteuse n, $n \in C_i$. Ensuite, le SNR du $i^{\text{ème}}$ SU sur la porteuse n peut être écrit comme

$$\Gamma_{i,n}^{\mathsf{UL}} = \frac{p_{i,n}\hat{b}_i\xi_{i,n}^{-1}G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2}, \tag{26}$$

où $\hat{b}_i = b_{max}b_i$, b_{max} et b_i représentent respectivement la perte d'espace libre et le gain de faisceau du satellite secondaire [2], $G^{\mathsf{SU}}(\theta_i)$ indique le gain d'antenne de l'utilisateur du satellite, θ_i désigne l'angle d'axe hors axe à partir de la ligne de pointage qui est illustrée en Fig. 3, $\sigma_{i,n}$ indique la puissance du bruit et $\xi_{i,N}$ est l'atténuation de la pluie entre l'utilisateur $i^{\text{ème}}$ et le satellite secondaire qui a la distribution logarithmique normale, c'est-à-dire $ln(\xi_{dB}) \sim \mathcal{N}(\mu, \hat{\sigma})$[2].

Ensuite, la somme des taux moyens de tous les utilisateurs de satellites peut être écrit comme suit:

$$\bar{R}^{\mathsf{UL}} = \sum_{i,n\in C_i}\int_1^{+\infty} W\log_2\left(1+\Gamma_{i,n}^{\mathsf{UL}}\right) f_{\Xi}(\xi_{i,n})d\xi_{i,n}, \tag{27}$$

où $f_{\Xi}(\xi_{i,n})$ est la fonction de densité de probabilité (PDF) d'atténuation de la pluie du satellite $\xi_{i,n}, \xi_{i,n} > 1$, [2] et W est bande passante de porteuse.

L'interférence moyenne causée par l'utilisateur satellite $i^{\text{ème}}$ au satellite primaire sur la porteuse n peut être calculée comme

$$\bar{I}_{i,n} = p_{i,n}\hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) \int_1^{+\infty} \frac{f_{\Xi}(\xi_{i,n}^{\mathsf{P}})}{\xi_{i,n}^{\mathsf{P}}} d\xi_{i,n}^{\mathsf{P}}. \tag{28}$$

Ensuite, le problème d'allocation des ressources considéré peut être énoncé comme suit:

$$\underset{\{p_{i,n},\theta_i\}}{\text{maximiser}} \quad \bar{R}^{\mathsf{UL}} \tag{29}$$

$$\text{sujet à} \quad \bar{I}_{i,n} \leq \bar{I}_{i,n}^{\mathsf{TH}}, \forall i = 1,..,K, n \in C_i, \tag{30}$$

$$\sum_{n \in C_i} p_{i,n} \leq P_i^{max}, \forall i = 1,..,K, \tag{31}$$

$$p_{i,n} \geq 0, \forall i = 1,..,K, n \in C_i, \tag{32}$$

$$0 \leq \theta_i \leq \frac{\theta_{i3dB}}{2}, \forall i = 1,..,K, \tag{33}$$

où $\bar{I}_{i,n}^{\mathsf{TH}}$ indique le seuil d'interférence sur la porteuse n pour l'utilisateur i, P_i^{max} est la puissance maximale de l'utilisateur du satellite i, et θ_{i3dB} est l'angle 3dB de l'antenne de l'utilisateur du $i^{\text{ème}}$ satellite. Dans ce problème, (30) (31) et (32) dénotent les contraintes de puissance des utilisateurs satellites, et (33) capture les contraintes d'angle des utilisateurs de satellites.

0.3.2 Algorithmes d'allocation des Ressources

Pour résoudre le problème (29)-(33), nous proposons un algorithme itératif où nous optimisons séquentiellement l'allocation de puissance et les angles des utilisateurs de satellites dans chaque itération. Les détails de cet algorithme proposé sont présentés ci-dessous.

0.3.2.1 Allocation de Puissance pour les Angles des Utilisateurs Donnés

Lorsque les angles des utilisateurs satellites sont donnés, le problème d'optimisation étudié devient le problème d'allocation de puissance suivant

$$\underset{\{p_{i,n}\}}{\text{maximiser}} \quad \sum_{i,n \in C_i} \int_1^{+\infty} W \log_2 \left(1 + \frac{p_{i,n}\hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2}\right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n} \tag{34}$$

$$\text{sujet à} \quad a p_{i,n}\hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) \leq \bar{I}_{i,n}^{\mathsf{TH}}, \forall i = 1,..,K, n \in C_i, \tag{35}$$

$$\sum_{n \in C_i} p_{i,n} \leq P_i^{max}, \forall i = 1,..,K, \tag{36}$$

$$p_{i,n} \geq 0, \forall i = 1,..,K, n \in C_i, \tag{37}$$

où a désigne l'atténuation moyenne de la pluie du satellite, qui peut être calculé comme

$$a = \int_{1}^{+\infty} \frac{f_{\Xi}(\xi)}{\xi} d\xi. \tag{38}$$

En exploitant sa structure décomposée, nous pouvons décomposer le problème (34) dans les sous-problèmes K suivants

$$\underset{\{p_{i,n}\}}{\text{maximiser}} \quad \sum_{n \in C_i} \int_{1}^{+\infty} W \log_2 \left(1 + \frac{p_{i,n} \hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2} \right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n} \tag{39}$$

$$\text{sujet à} \quad a p_{i,n} \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) \leq \bar{I}_{i,n}^{\mathsf{TH}}, \forall n \in C_i, \tag{40}$$

$$\sum_{n \in C_i} p_{i,n} \leq P_i^{max}, \tag{41}$$

$$p_{i,n} \geq 0, \forall n \in C_i. \tag{42}$$

Nous pouvons vérifier que la fonction objective de chaque sous-problème i est une fonction concave des puissances d'émission. Par conséquent, ces sous-problèmes sont des problèmes d'optimisation convexe, qui peuvent être résolus de manière optimale en utilisant la méthode Lagrangienne à double-base.

Dans ce but, le Lagrangien du problème (39) peut être écrit comme

$$\mathcal{L} = \sum_{n \in C_i} \int_{1}^{+\infty} W \log_2 \left(1 + \frac{p_{i,n} \hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2} \right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n} - \delta_i \left(\sum_{n \in C_i} p_{i,n} - P_i^{max} \right) - \sum_{n \in C_i} \lambda_{i,n} \left(a p_{i,n} \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) - \bar{I}_{i,n}^{\mathsf{TH}} \right), \tag{43}$$

où $\lambda_{i,n}$ et δ_i sont des multiplicateurs de Lagrange associés respectivement aux contraintes d'interférence et de puissance.

Ensuite, nous étudions les conditions d'optimalité de Karush-Kuhn-Tucker pour la solution optimale d'allocation de puissance de (39) comme suit:

$$\frac{\delta \mathcal{L}}{\delta p_{i,n}} = \int_{1}^{+\infty} W \frac{\hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\left(\sigma_{i,n}^2 + p_{i,n} \hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i) \right) \ln 2} f_{\Xi}(\xi_{i,n}) d\xi_{i,n} - \delta_i - \lambda_{i,n} a \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) = 0. \tag{44}$$

Nous pouvons vérifier que le premier terme dans (44) est une fonction décroissante de $p_{i,n}$. Par conséquent, pour des valeurs données des variables duales $\lambda_{i,n}$ et δ_i, nous pouvons résoudre (44) de manière optimale en utilisant la méthode de la bissection.

De plus, nous pouvons utiliser la méthode du sous-gradient standard pour actualiser itérativement les variables duales en fonction de leurs valeurs optimales comme suit:

$$\lambda_{i,n}(t+1) = \left[\lambda_{i,n}(t) + e_{i,n} \left(a p_{i,n} \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) - \bar{I}_{i,n}^{\mathsf{TH}} \right) \right]^+, \tag{45}$$

$$\delta_i(t+1) = \left[\delta_i(t) + \bar{s}_i\left(\sum_{n\in C_i} p_{i,n} - P_i^{max}\right)\right]^+, \tag{46}$$

où $[x]^+ = \max(x, 0)$, t indique l'index d'itération, $\bar{s}_i$ et $e_{i,n}$ sont les pas.

L'algorithme d'allocation de puissance optimale globale est résumé dans Algorithme 4, qui peut converger vers la solution optimale globale du problème (34)-(35).

Algorithm 4 Allocation de Puissance

1: **Entrée:** Initialiser les multiplicateurs non négatifs de Lagrange $\lambda_{i,n}$'s et δ_i's aléatoire.
2: **Sortie:** Allocation de puissance $p_{i,n}$.
3: **Initialiser:** L'itération: $t = 1$.
4: **repeat**
5: Mettre à jour allocation de puissance $p_{i,n}$'s comme l'équation (44).
6: Mettre à jour Lagrange multiplicateur $\lambda_{i,n}$'s et δ_i's comme dans (45) et (46), respectivement.
7: Mettre à jour indice d'itération: $t = t + 1$.
8: **until** Convergence

0.3.2.2 Optimisation des Angles des Utilisateurs des Satellites pour une Solution d'allocation de Puissance Donnée

Pour une solution d'allocation de puissance donnée, nous pouvons observer que la fonction objectif et l'interférence moyenne (c'est-à-dire le côté gauche des contraintes d'interférence (30)) sont en baisse avec l'augmentation de l'angle de l'utilisateur θ_i. Par conséquent, pour obtenir une valeur optimale pour (29), il suffit de déterminer la valeur minimale de θ_i tout en veillant à ce que les contraintes d'interférences moyennes (30) puissent être maintenues.

Algorithm 5 Maximisation de la Somme des Taux Moyen (ASRM)

1: **Entrée:** θ_i's est choisi au hasard.
2: **Sortie:** allocation de puissance $p_{i,n}$ et les angles des utilisateurs θ_i's.
3: **Initialiser:** Les valeurs initiales de θ_i's sont choisies aléatoirement.
4: **for** chaque utilisateur du système **do**
5: **repeat**
6: Mettre à jour l'allocation de puissance $p_{i,n}$'s en utilisant Algorithme 4.
7: Mettre à jour les angles des utilisateurs satellites θ_i's quand $p_{i,n}$ est fixe.
8: **until** Convergence
9: **end for**

Avec l'allocation de puissance optimale obtenue en utilisant l'Algorithme 4 et les angles des utilisateurs satellites optimaux donnés quand $p_{i,n}$ est fixe, notre algorithme proposé est résumé dans Algorithme 5.

0.3.3 Résultats Numériques

Nous considérons un système à deux satellites où le satellite secondaire a sept faisceaux, deux utilisateurs par faisceau et chaque utilisateur de satellite secondaire est alloué trois porteuses, sauf indication contraire. Nous adoptons le modèle de canal satellite dans [2] et le modèle d'antenne de l'utilisateur du satellite est donné dans [53]. Le seuil d'interférence sera généré aléatoirement dans l'intervalle $\left(0, I_{i,n}^{\mathsf{max}}\right)$, où $I_{i,n}^{\mathsf{max}} = P_i^{\mathsf{max}} G(\alpha_i) a\hat{b}_i^{\mathsf{P}}$ représente l'interférence maximale que l'utilisateur i peut créer pour le satellite primaire sur la porteuse $n \in C_i$ avec sa puissance maximale P_i^{max}. Le paramétrage de notre simulation est résumé dans le Tableau 2. Nous supposons que l'angle de chaque utilisateur vers les deux satellites est égal à $\alpha_i = 4.2°$ (comme dans le système à deux satellites Anik-F3 et ViaSat-1). Pour la comparaison des performances avec l'algorithme proposé, nous considérons les deux schémas suivants

- Zéro degré fixe (FZD): pour ce schéma, l'angle de tout utilisateur de satellite secondaire i (c.-à-d., θ_i) est toujours fixé égal à zéro tandis que la solution d'allocation de puissance est déterminée en utilisant l'Algorithme 4.

- Zéro degré fixe et allocation uniforme de puissance (FZDUPA): pour ce schéma, l'angle de tout utilisateur de satellite secondaire i (c'est-à-dire, θ_i) est toujours égal à zéro alors que l'allocation de puissance uniforme est effectuée comme suit:

$$p_{i,n} = \begin{cases} \frac{P_i^{max}}{|C_i|} & \text{if } \frac{P_i^{max}}{|C_i|} G^{\mathsf{SU}}(\alpha_i) < \frac{\bar{I}_{i,n}^{\mathsf{TH}}}{a\hat{b}_i^{\mathsf{P}}}, \forall n \in C_i \\ \min_{n \in C_i} \{ \frac{\bar{I}_{i,n}^{\mathsf{TH}}}{a\hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\alpha_i)} \} & \text{if sinon.} \end{cases} \tag{47}$$

Le SNR moyen est défini comme

$$\text{SNR moyen} = \frac{a\hat{b}_i G(\alpha_i) P_i^{\mathsf{max}}/2}{\sigma_{i,n}^2}, \tag{48}$$

où a est le gain moyen du canal satellite donné en (38).

Table 2: Paramètres du système de simulation (liaison montante)

Paramètres	Valeur
Orbite	GEO
Rayon de la terre	6371km
La fréquence	Ka Band
Nombre de faisceaux	7
Nombre de porteuses	3
Nombre d'utilisateurs par faisceau	2
Diamètre du faisceau	250km
Satellite $3dB$ angle	0.4^o
Moyenne d'atténuation de la pluie	-2.6dB
Variance d'atténuation de la pluie	1.63dB
FL perte d'espace libre	210dB
Diamètre réflecteur de SU	0.5m
Efficacité de l'antenne de SU	0.6
Puissance maximale de SU	10W
Bande passante	16.6Mhz

Dans Fig.4, nous montrons la somme des taux moyen par rapport à l'augmentation du seuil de brouillage (IIT) où l'IIT est défini comme

$$\mathrm{IIT} = \frac{\overline{I}_{i,n}^{\mathsf{TH}} - \tilde{I}_{i,n}}{\min_i a\hat{b}_i^{\mathsf{P}}}, \tag{49}$$

où $\tilde{I}_{i,n}$'s sont choisis aléatoirement dans $\left(0, I_{i,n}^{\mathsf{max}}\right)$, où $I_{i,n}^{\mathsf{max}} = P_i^{\mathsf{max}} G(\alpha_i) a\hat{b}_i^{\mathsf{P}}$ pour chaque utilisateur et chaque opérateur. Nous pouvons alors calculer le seuil d'interférence moyen $\overline{I}_{i,n}^{\mathsf{TH}}$ basé sur $\tilde{I}_{i,n}$ et IIT. Dans notre simulation, pour une valeur donnée d'IIT, chaque utilisateur et la porteuse auront le même IIT. Nous pouvons voir que la somme des taux moyen atteint augmente avec l'IIT (avec le seuil d'interférence aussi). En outre, notre ASRM Alg. se traduit par un meilleur somme des taux moyen que ceux dus aux régimes FZD et FZDUPA.

Dans Fig. 5, nous montrons les variations de la somme des taux moyens avec la puissance maximale des utilisateurs du satellite dû à l'algorithme ASRM proposé ainsi que les schémas FZD et FZDUPA. Comme nous pouvons le voir sur cette figure, la somme des taux moyens obtenu à partir de l'algorithme ASRM est beaucoup plus élevé que ceux dus aux programmes FZD et FZDUPA. En outre, la somme des taux moyens obtenus par les trois régimes augmentent avec la puissance maximale des utilisateurs des satellites avant de saturer à une puissance maximale des utilisateurs suffisamment grande. Ceci est dû au fait les contraintes d'interférence moyennes au niveau du satellite primaire limitent les pouvoirs d'émission admissibles des utilisateurs du satellite.

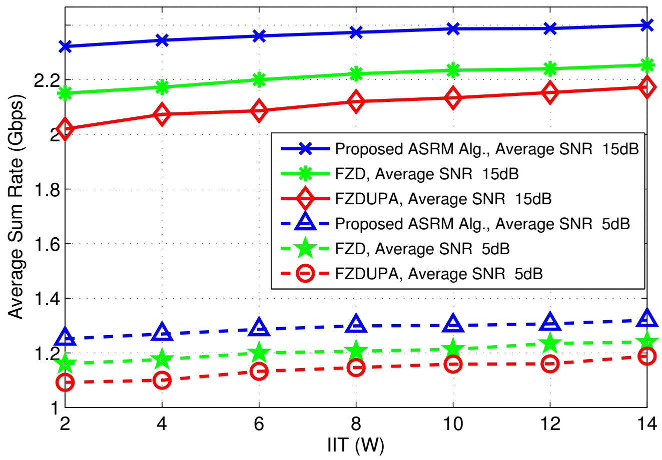

Figure 4: La somme des taux moyens vs incrément de seuil d'interférence pour K=14 utilisateurs, J=7 faisceaux

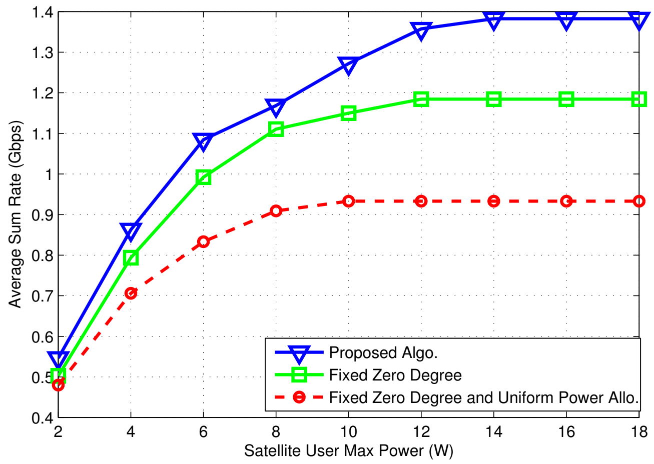

Figure 5: La somme des taux moyens vs la puissance maximale de l'utilisateur du satellite pour K = 14, J=7, SNR moyenne = 15dB, $\overline{I}^{\mathsf{TH}}_{i,n}$ sont définies aléatoirement.

0.4 Conclusion

Dans ce mémoire, nous avons développé quelques algorithmes d'allocation de ressources pour la gestion avancée des ressources radio dans les systèmes à satellites. La conception a été réalisée pour le système à satellite unique et le système à deux satellites coexistants.

Pour le système mono-satellite à faisceaux multiples, nous nous sommes penchés sur la formation conjointe de faisceaux descendants, l'attribution de porteuses et à des problèmes d'ordonnancement

des utilisateurs d'un système de satellites à des faisceaux multiples et des porteuses multiples qui visent à maximiser la somme des taux du système ou la valeur de la somme des utilités. Ensuite, nous avons développé deux algorithmes itératifs, à savoir l'algorithme de la somme des taux maximale (MSRA) et l'algorithme d'utilité maximale (MUA), pour résoudre les deux problèmes sous-jacents. Les résultats numériques ont montrent que l'algorithme MSRA peut atteindre jusqu'à 20 % de gain de débit par rapport à l'algorithme MUA alors que le dernier réalise un partage de ressources plus équitable partage pour les utilisateurs.

Pour le système à double satellite coexistant, nous avons proposé le cadre de répartition des ressources de la liaison montante basée sur la radio cognitive qui maximise le taux moyen de somme du système en optimisant les puissances d'émission et les angles des utilisateurs secondaires tandis qu'en maintenant les contraintes d'interférence au niveau du satellite primaire. Nous avons ensuite effectué des études numériques pour l'évaluation des performances et la comparaison de l'algorithme proposé et d'autres méthodes conventionnelles régimes. Des résultats numériques ont montré que l'algorithme proposé peut atteindre environ 10-20% de gain de somme par rapport à des schémas conventionnels avec des angles d'utilisateurs secondaires nulls et/ou une allocation de puissance uniforme.

Abstract

Due to the constantly growing satellite traffic, more and more satellites have been launched into the orbit. This leads to rising congestion on both the earth orbit and radio spectrum, which results in increasing radio-frequency interference (RFI) in the satellites communications. Moreover, spectrum reuse for communications in different beams of multibeam satellites, which generates co-channel interference, can result in degradation of communication reliability and performance if the interference is not managed appropriately. To tackle the interference mitigation and better exploit satellite radio resources, we have proposed some advanced resource allocation techniques for satellite communications. Specifically, we have developed radio resource management frameworks in two satellite communications settings, namely the single satellite system and the co-existing dual satellite system.

For the single multi-beam satellite system, we have studied the joint beamforming, carrier allocation, and user scheduling problem which aims to maximize the system sum rate and sum utility. To tackle the two underlying problems, two corresponding iterative resource allocation algorithms have been developed. In both algorithms, the advanced weighted minimum mean square error (WMMSE) beamforming scheme has been employed to determine the beamformers based on which carrier allocation and user scheduling design can be addressed. Extensive numerical results have demonstrated the efficiency and desirable performance of the proposed algorithms.

For the co-existing dual satellite system, a cognitive radio based reverse-link resource allocation framework has been developed where the two satellites have been treated as the primary and secondary satellites, respectively. The resource allocation design for this setting involves the optimization of power allocation and users' antenna angles to maximize the average system sum rate considering maximum power and interference protection constraints. To accomplish this design, we have derived the optimal power allocation solution for given secondary users' angles and derived the optimal secondary users' angles for a given power allocation solution. Then, we have proposed an iterative resource allocation algorithm based on these derivations to address the considered problem. Finally, we have carried out numerical studies to investigate the performance of the proposed algorithm which have confirmed the performance superiority of the proposed algorithm compared to other conventional resource allocation approaches.

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Glossary

Abbreviations

ASRM	Average sum rate maximization
BSS	Broadcast satellite service
CSI	Channel state information
FSS	Fixed satellite service
FZD	Fixed zero degree
FZDUPA	Fixed zero degree and uniform power allocation
GEO	Geostationary earth orbit
GPS	Global positioning service
IIT	Increment of interference threshold
KKT	Karush-Kuhn-Tucker
LCMV	Linearly constrained minimum variance
LEO	Low earth orbit
MEO	Medium earth orbit
MIMO	Multiple input multiple output
MISO	Multiple input single output
MMSE	Minimum mean square error
MSE	Mean square error
MSRA	Max sum rate algorithm
MSRP	Max sum rate problem
MSS	Mobile satellite service
MUA	Max utility algorithm
MUP	Max utility problem
MVDR	Minimum variance distortionless response
PDF	Probability density function

QoS	Quality of service
$SINR$	Signal to interference plus noise ratio
SNR	Signal to noise ratio
SU	Satellite user
UL	Uplink
$WMMSE$	Weighted minimum mean square error
ZF	Zero forcing

Notations

α	A constant in $0 < \alpha < 1$
α_i	Angle seen from user i towards two satellites
$\bar{I}_{i,n}$	Average interference caused by satellite user i on carrier n
$\bar{I}_{i,n}^{\mathsf{TH}}$	Interference threshold on carrier n
$\bar{R}^{\mathsf{UL}}$	Average sum rate on the uplink
$\bar{R}_i$	Long-term average rate of user i on the downlink
$\bar{R}_{i,n}^{\mathsf{UL}}$	Average data rate of user i on carrier n on the uplink
$\bar{s}_i, e_{i,n}$	Step sizes
β_i	Weight parameter
η	Antenna efficiency of satellite user
$\eta_{i,n}$	Zero mean Gaussian noise at user i on carrier n
γ_i	Inverse mapping of gradient map
$\Gamma_{i,n}$	Signal to interference plus noise ratio of user i on carrier n on the downlink
$\Gamma_{i,n}^{\mathsf{UL}}$	Signal to noise ratio of user i on carrier n on the uplink
$\hat{\sigma}^2$	Rain fading variance
$\hat{b}_i$	Product of free space loss and secondary satellite beam gain
$\hat{b}_i^{\mathsf{P}}$	Product of free space loss and primary satellite beam gain
$\hat{r}_i$	Receive signal after applying receive detection weight parameter U_i
$\lambda_{i,n}, \delta_n$	Lagrange multipliers
μ	Rain fading mean
μ_i^*	Lagrange multiplier
σ^2	Noise variance in the satellite downlink
$\sigma_{i,n}^2$	Noise power on carrier n adopted by user i
$\mathbf{h}_{i,n}$	Satellite channel gain from satellite to user i on carrier n

$\mathbf{w}_{i,n}$	Transmit beamformer vector
θ	Angle between satellite user and its satellite
θ_i	Angle between satellite user i and its satellite
θ_{3dB}	3dB angle satellite user's antenna
θ_{i3dB}	3dB angle i^{th} satellite user's antenna
$\tilde{R}_{ib}$	Rate achieved by user i when it is served by beamformer b
$\xi_{i,n}$	Rain fading between user i and secondary satellite
$\xi_{i,n}^{\mathsf{P}}$	Rain fading between user i and primary satellite
a	Average satellite rain fading gain
$a_{i,n}$	Binary carrier allocation variable
b_i^{P}	Primary satellite beam gain
b_i	Secondary satellite beam gain
b_{max}	Free space loss
c	Speed of light
C_i	Set of carrier allocated to user i
c_i	Cost function of satellite user i
D	Reflector diameter of satellite user
f	Frequency
G	Group size
G^{max}	Maximum gain of satellite user's antenna
G_{dBi}^{max}	Maximum gain of satellite user's antenna in dBi
G_{dBi}^{SU}	Antenna gain of satellite user in dBi
i	Satellite user index
$I_{i,n}$	Instantaneous interference caused by user i to the primary satellite
J	Number of satellite beams
j	Satellite beam index
K	Number of satellite users
N	Number of carriers
n	Carrier index
P_i^{max}	Max power of satellite user
$p_{i,n}$	Transmit power of user i on carrier n
P_{tot}	Total power of satellite

R	Sum rate on the downlink
R_i	Achieved rate of user i on the downlink
$r_{i,n}$	Received signal of user i on carrier n
S	Set of scheduled users
s_i	Data symbol transmitted to user i
S_j	Set of users in beam j
t	Iteration index
U_i	Receive detection weight
u_i	Utility function of satellite user i
u_{tot}	Sum utility

Chapter 1

Introduction

1.1 Motivations

Due to the ever-increasing traffic demand, more and more satellites have been deployed in recent years. The deployed satellites can be in one of the popular earth's orbits such as geostationary (GEO), medium earth orbit (MEO) or low earth orbit(LEO) and these satellite can provide different kinds of services including Fixed Satellite Service (FSS), Broadcast Satellite Service (BSS), Mobile Satellite Service (MSS), Maritime Mobile Satellite Service, and Global Positioning Service (GPS) [4]. In general, a satellite system can achieve vast geographic coverage which is much larger than that due to a terrestrial wireless communication system. In fact, a small number of satellites can cover almost entire continent or even entire globe. For example, a GEO satellite such as Anik-F2 and ViaSat-1 can cover most of the North America's surface [4, 5] and the future ViaSat-2 can provide seven times increase in terms of coverage area compared to ViaSat-1 when it is launched in 2017 [4]. Hence, a satellite system is superior to its terrestrial counterpart from the coverage viewpoint.

In order to enhance the capacity to cope with increasing satellite traffic, the spot beam principle has been widely adopted in multibeam satellite communication systems as illustrated in [6, 7]. Moreover, adoption of the multibeam technique also allows to realize frequency reuse over different beams, which can significantly enhance the system throughput. In particular, the throughput of Viasat-1 was announced to be 134Gbps, which is currently the communication satellite with highest throughput [4]. Furthermore, the deployment of spot beam facilitates multistream transmission with one stream in each beam [2, 4]. Also, the multibeam approach can lead to a higher satellite antenna gain which results in curtailment in the aperture angle of the antenna beam. This also implies that satellite users can utilize smaller aperture antennas [4]. However, widespread adoption of multibeam antennas and deployment of multiple satellites operating on the same or adjacent frequency bands and the same/overlapping geographic coverage area require advanced techniques for interference mitigation and spectrum management.

For radio resource management, MIMO beamforming is a promising approach [8] to mitigate the interference among different beams in multibeam satellites. This is because if two (or

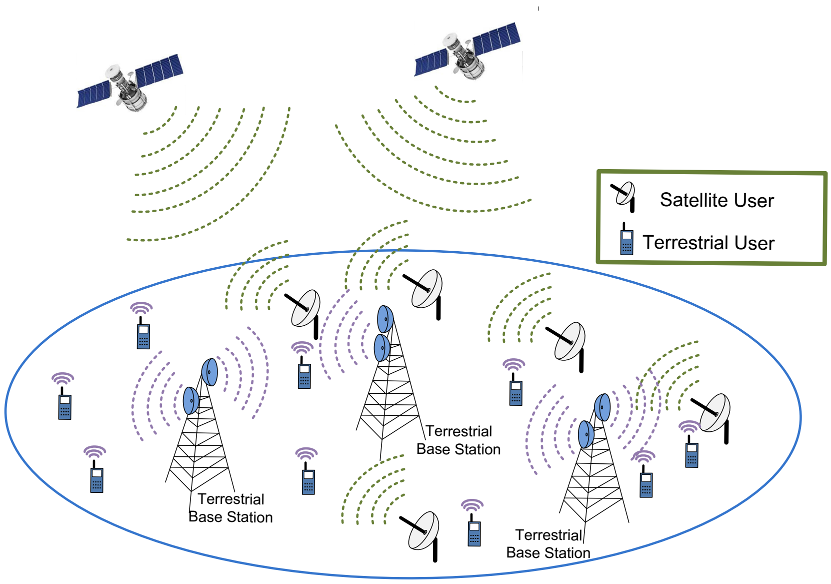

Figure 1.1: Satellite and terrestrial communications

more) beams are allocated the same frequency band then inter-beam interference occurs due to nonzero gains of antenna sidelobes, which can severely degrade the communication reliability and performance. Moreover, modern satellite systems transmit data over multiple carriers to serve thousands of users. Hence, flexible carrier allocation and user scheduling design play important roles in interference management and spectrum utilization enhancement. Joint optimization of beamforming, power allocation, carrier allocation and user scheduling is, therefore, a critical research task in the multibeam satellite system.

In addition, satellite communications can also induce the RF interference to other communication systems such as terrestrial microwave systems or other satellites operating on the same frequency band over the same or overlapping coverage area. The cognitive radio based resource allocation approach can be employed to mitigate co-channel interference where these communication systems can be considered primary and secondary systems depending on their communication and spectrum access priorities. In general, the cognitive radio technique can be a potential candidate to lessen the interference and enable reliable and friendly co-existence of terrestrial-satellite systems or multiple satellite systems as shown in Fig. 1.1.

1.2 Literature Review

In this section, we conduct literature survey on existing radio resource management techniques in satellite communications. In particular, our review focuses on two important scenarios, namely the single satellite system and co-existing multi-satellite system.

1.2.1 Single Satellite System

By employing a multibeam antenna in the satellite, a multibeam satellite communication system can potentially increase the system throughput. However, concurrent multibeam communications on the same frequency band create co-channel interference, which can severely degrade the communication reliability and performance if not managed appropriately. Here, the multi-antenna beamforming and power allocation techniques can be employed to mitigate the co-channel interference and enhance the spectrum utilization. In fact, resource allocation and beamforming design have been active research topics in multibeam satellite communications in recent years. Particularly, power and beamforming optimization for the single-carrier satellite system has been studies in several existing works [2, 9–24]. The study in [9] proposes the power control scheme for a satellite system where power adaptation is based on the MMSE channel estimation approach. In [10], power allocation for downlink multibeam satellite communications is investigated where the design objective is a general capacity matching function subject to the power constraints. The study in [11] aims to maximize the downlink satellite system throughput by optimizing the transmit power and queuing delays. The work [12] considers the optimal power allocation for land mobile satellite communications where the Rician fading model and adaptive modulation are assumed and the study aims at maximizing the capacity under QoS constraints. In [13], the power allocation problem which minimizes the number of subscribers not achieving their desired QoS subject to the satellite power constraint is studied.

There is also a good number of works on beamforming design for the single-satellite system. In particular, the work [2] addresses the joint power and beamforming design for the single-carrier system in which a general objective function is maximized subject to linear and non linear power constraints. Another resource allocation problem that aims at minimizing the satellite's transmit power with the secrecy rate constraint is considered in [14, 15]. The work [14] studies the Zero-Forcing (ZF) beamforming while the paper [15] proposes an iterative algorithm combining the semi-definite programming and gradient methods to optimize the beamformers. Robust beamforming design is tackled in [16] assuming the phase uncertainty. The frame-based precoding is studied in [17] which aims at maximizing the system sum rate under per antenna power constraints. Furthermore, the work [18] investigates the beamformers that maximize two different objectives, namely system throughput and energy efficiency where sub-optimal solutions are obtained by using the MMSE beamforming technique. The MMSE based beamforming design is also conducted in [19] for the multibeam satellite system.

The beamformer optimization for satellite throughput maximization is studied in [20] where the performance of linear precoder with optimal nonlinear precoding in the forward link and MMSE based receiver for the return link direction are considered. The work [21] studies the rate balancing problem through joint downlink power allocation and beamforming where generic linear power constraints considering traveling wave tube amplifiers are accounted for in this study. In [22], the joint linear precoding and ground beamforming at the gateway are considered for the forward link of a multibeam satellite where the ZF and MMSE precoders are adopted. Finally, in [23] and [24], the multi-gateway satellite communications scenario is considered where each gateway serves a cluster of satellite beams. For the precoder design in [23], each gateway aims to maximize its throughput under the gateway power constraint where both non-cooperative and cooperative gateway schemes are considered. The study in [24], on the other hand, adopts the smart gateway switching approach in multibeam satellite to better exploit the radio resources.

Resource allocation for multi-carrier satellite systems has also been conducted in several works [25–32]. In particular, the work [25] studies the resource allocation for the uplink multi-carrier multibeam satellite where the authors propose an algorithm for power and carrier allocation to achieve users' SINR targets with minimum power. The work [26] also considers this SINR balancing problem but for the downlink direction.

The problem of joint power and bandwidth allocation is studied in [27] where the system throughput is maximized subject to the delay constraint. Another joint power and bandwidth allocation studies are conducted in [28, 29]. Specifically, the work [29] aims to match the bit rate represented by a general n^{th} order deviation cost function where fair cost objective function is adopted in this research. Moreover, the work [28] focuses on throughput optimization as well as the rate matching where two resource allocation schemes are proposed for efficient satellite resource utilization under per-beam SINR constraints. The design objective of [30] is to maximize the satellite system throughput through carrier allocation optimization. The paper [31] deals with dynamic bandwidth allocation where traffic prediction is used in the developed dynamic bandwidth allocation scheme. Finally, to maximize the multibeam satellite throughput in the downlink direction, beam hopping optimization considering adaptive coding and modulation is performed in [32].

1.2.2 Co-existing Multiple-Satellite System

The fact that more and more satellites have been deployed in recent years has increased the risks of co-channel interference between satellite and terrestrial networks or among different satellites. Discussions of some possible interference scenarios and the employment of cognitive radio techniques for spectrum and interference management are studied in [33–35]. In particular, the interference management for the satellite and terrestrial systems operating on the overlapping spectrum is investigated in [36–43]. In [36], a cognitive radio based resource allocation scheme is adopted for interference management in the terrestrial-satellite co-existing scenario where a multi-objective optimization problem is studied considering the interference constraints at the terrestrial receivers. In [37], the authors propose a beamforming algorithm for the terrestrial network which aims to maximize the SINR of a terrestrial user while maintaining the interference at the primary satellite terminals below a pre-defined threshold. In [38], resource allocation algorithms are proposed for both downlink and uplink communications of a multi-carrier satellite system whose design objective is sum rate maximization subject to interference constraints at the terrestrial network and of the transmit power.

The work [39] studies the power allocation problem whose objective is to maximize the rate of the terrestrial link while guaranteeing the communication quality of the satellite link. In [40], the uplink satellite power allocation problem is studied considering the interference protection constraints for the terrestrial system. The paper [41] considers the hybrid terrestrial-satellite system where the authors explore different system and payload architectural possibilities for partitioning ground and space processing required for the beamforming design to achieve better flexibility and efficiency. By varying the satellite interference power, the work [42] studies the outage performance of a cognitive hybrid terrestrial-satellite system where the primary satellite communication network and the secondary terrestrial mobile network can coexist under the appropriate interference protection constraint. In [43], a genetic based carrier allocation and user scheduling algorithm is proposed to determine the solution of the rate matching problem.

Radio resource allocation for the co-existence of multiple-satellite systems has also been studied in the literature [44–50]. In [44], a joint beamforming and user scheduling algorithm is proposed based on the semi-orthogonal interference-aware user scheduling principle and ZF beamforming. The work [45] also considers beamforming optimization for the dual cognitive satellite system where minimum variance distortionless response (MVDR) and linearly constrained minimum variance (LCMV) schemes are adopted in the beamforming design while the carrier assignment solution is determined by the Hungarian algorithm. Also for the dual co-existing satellite system, three different interference alignment schemes are studied in [50] which aim to mitigate the co-channel interference.

The study in [46] proposes a beamhopping algorithm in a dual coexisting satellite system to enhance the spectral efficiency while power allocation and exclusive zone scheme are derived to maintain the interference constraint for the primary system. The work [49] develops the interference estimation technique which is then used to engineer the coexistence in the dual satellite system. In [48], the authors derive the cognitive zone for the satellite operating in the 17.3-17.7GHz frequency band. In [47], the authors study the coexisting GEO and MEO satellite and an adaptive power allocation framework is proposed for the MEO satellite to maximize its capacity and maintain the interference limit of the GEO satellite in both uplink and downlink scenarios.

1.3 Research Objectives and Contributions

The overall objective of this thesis is to develop advanced resource allocation techniques for satellites communications in two different scenarios, namely the multibeam single-satellite and the dual coexisting satellite systems. Specifically, our research contributions can be summarized as follows.

In the first contribution, we consider the joint beamforming, carrier allocation and user scheduling problem for the downlink multi-carrier multibeam satellite system. The resource allocation design aims to optimize the system sum rate and sum utility. Toward this end, we develop two novel iterative algorithms, namely Max Sum Rate Algorithm (MSRA) and Max Utility Algorithm (MUA), to solve the underlying problems. In both proposed algorithms, we design the beamfomers to maximize the sum rate and sum utility, respectively by using the advanced weighted minimum mean square error (WMMSE) beamforming approach [1]. In addition, we employ these beamforming solutions to address the corresponding scheduling design problems. Extensive numerical studies are then conducted to evaluate the rate/fairness performance of the proposed MUA and MSRA algorithms. Specifically, it is shown that the MSRA algorithm can achieve higher throughput than that due to the MUA while the MUA algorithm results in better fairness of the users. In addition, we also analyze the impacts of different system parameters on the achievable performance of the proposed algorithms.

In the second contribution, we consider the cognitive radio based resource allocation for the uplink dual multi-carrier satellite system. Our design aims to maximize the average system sum rate by optimizing the power allocation and users' angles of the secondary satellite while maintaining the average interference constraints at the primary satellite. We develop an iterative algorithm to solve the underlying problem based on decoupled power allocation and secondary users' angles optimization. We show that our algorithm converges and achieves at least local optimal solution. We then study the performance of the proposed algorithm via extensive simulation results. The numerical results demonstrate the significant performance gains compared to other conventional designs, namely those with zero secondary users' angles and/or uniform power allocation.

1.4 Thesis Outline

The remaining of this thesis is structured as follows. Chapter 2 presents some technical background related to resource allocation design conducted in this thesis. Specifically, we will review fundamental optimization techniques including Karush-Kuhn-Tucker necessary conditions, Lagrange duality, convex optimization, basics of the WMMSE beamforming method, and user scheduling.

Chapter 3 describes the system model and mathematical formulation of the joint downlink beamforming, power allocation, user scheduling, and carrier allocation for the multibeam satellite system. We describe two different optimization problems, namely max sum rate optimization and max utility optimization and the corresponding two resource allocation algorithms to tackle these optimization problems. Finally, numerical studies to illustrate effectiveness of the proposed algorithms are conducted.

Chapter 4 presents a cognitive radio based uplink resource allocation framework for the dual satellite system. Our design aims at maximizing the average sum rate where we optimize the secondary satellite users' powers and angles toward the primary satellite. The proposed iterative algorithm to solve the underlying optimization problem is then presented followed by numerical studies to demonstrate the performance of the proposed design framework. Finally, conclusion remarks are presented in Chapter 5 together with the discussions of some future research directions.

Chapter 2

Background

This chapter presents some fundamental background which are used for various resource allocation design in this thesis. Specifically, we describe some basics on optimization theory, Weighted Minimum Mean Square Error (WMMSE) beamforming techniques, and proportional fair user scheduling.

2.1 Optimization Theory

This section discusses the fundamentals of mathematical optimization. To be specific, we will discuss the general form of an optimization problem, Lagrange dual decomposition method, Karush-Kuhn-Tucker necessary optimal conditions, and convex optimization.

2.1.1 General Form of an Optimization Problem

General form of an optimization problem can be written as [51]:

$$\underset{x}{\text{minimize}} \quad f_0(x) \tag{2.1}$$

$$\text{subject to} \quad f_i(x) \leq 0, \qquad \forall i = 1, .., m, \tag{2.2}$$

$$h_i(x) = 0, \qquad \forall i = 1, .., p. \tag{2.3}$$

In this problem, $f_0 : \mathbb{R}^n \to \mathbb{R}$ denotes the objective or cost function, $f_i : \mathbb{R}^n \to \mathbb{R}$ are inequality constraint functions, $h_i : \mathbb{R}^n \to \mathbb{R}$ are equality constraint functions, and $x \in \mathbb{R}^n$ is the optimization variable.

Solving an optimization problem is equivalent to find the values of x that minimize the cost function $f_0(x)$ while guaranteeing the inequality constraints $f_i(x) \leq 0, \forall i = 1, .., m$ and equality constraints $h_i(x) = 0, \forall i = 1, .., p$. The *domain* $\mathcal{D}$ of an optimization problem is defined as the set of values of x for which the definitions of functions $f_0(x)$, $f_i(x)$, and $h_i(x)$ are available

$$\mathcal{D} = \bigcap_{i=0}^{m} \mathbf{dom} f_i \cap \bigcap_{i=0}^{p} \mathbf{dom}\ h_i. \tag{2.4}$$

A value of $x \in \mathcal{D}$ for which all the constraints are met is called *feasible*. *Feasible set or constraint set* is defined as the set of all feasible values of x. If the feasible set is not empty, the problem (2.1)-(2.3) is called a feasible optimization problem, and it is infeasible optimization problem if otherwise. The following expression defines an optimal value of problem (2.1)-(2.3)

$$p^* = \inf\{f_0(x) \mid h_i(x) = 0, \forall i = 1, .., p, f_i(x) \leq 0, \forall i = 1, .., m\}. \tag{2.5}$$

2.1.2 Lagrange Dual Function and Lagrange Dual Problem

The Lagrangian $\mathcal{L} : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$ of the optimization (2.1)-(2.3) is given as [51]

$$\mathcal{L}(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x), \tag{2.6}$$

where λ_i's and ν_i's are called *Lagrange multipliers*. The vector λ and ν are referred to as *dual variables* or *Lagrange multiplier vectors*. The *Lagrange dual function* $g : \mathbb{R}^m \times \mathbb{R}^p \to \mathbb{R}$ is defined as

$$g(\lambda, \nu) = \inf_{x \in \mathcal{D}} \mathcal{L}(x, \lambda, \nu) = \inf_{x \in \mathcal{D}} \left(f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x) \right). \tag{2.7}$$

The *Lagrange dual problem* is then defined as

$$\underset{\lambda,\nu}{\text{maximize}} \qquad g(\lambda, \nu) \tag{2.8}$$

$$\text{subject to} \qquad \lambda \geq 0, \tag{2.9}$$

and problem (2.1)-(2.3) is referred to as a primal problem in this context. Suppose that the optimal objective value of (2.8)-(2.9) is d^* then the difference $p^* - d^*$ is referred to as the duality gap. We have *strong duality* when the duality gap is zero ($p^* = d^*$).

2.1.3 Karush-Kuhn-Tucker conditions

Let us denote x^* and (λ^*, ν^*) as the primal and dual optimal solution with strong duality condition. Then they will satisfy the Karush-Kuhn-Tucker (KKT) necessary conditions which are expressed as follows [51]

$$f_i(x^*) \leq 0, \qquad \forall i = 1, .., m, \tag{2.10}$$

$$h_i(x^*) = 0, \qquad \forall i = 1, .., p, \tag{2.11}$$

$$\lambda_i^* \geq 0, \qquad \forall i = 1, .., m, \tag{2.12}$$

$$\lambda_i^* f_i(x^*) = 0, \qquad \forall i = 1, .., m, \tag{2.13}$$

$$\nabla f_0(x^*) + \sum_{i=1}^{m} \lambda_i^* \nabla f_i(x^*) + \sum_{i=1}^{p} \nu_i^* \nabla h_i(x^*) = 0, \tag{2.14}$$

where ∇f denotes the gradient of f.

2.1.4 Convex Optimization

To facilitate the discussions of convex optimization, we first introduce some basic concepts, namely convex set and convex function. Specifically, a set S is called convex if it satisfies the following property

$$\varrho x_1 + (1 - \varrho) x_2 \in S, \forall x_1, x_2 \in S \text{ and } \varrho \in [0, 1]. \tag{2.15}$$

The meaning of (2.15) is that the line segment connects two points $x_1, x_2 \in S$ lies in S.

Moreover, function $f : \mathbb{R}^n \to \mathbb{R}$ is a convex function if **dom** f is a convex set and f satisfies the following property

$$f(\varrho x + (1 - \varrho) y) \leq \varrho f(x) + (1 - \varrho) f(y), \ \forall x, y \in \textbf{dom } f \text{ and } \varrho \in [0, 1]. \tag{2.16}$$

A convex optimization problem is a special case of the general optimization problem (2.1)-(2.3). In particular, the standard convex problem can be expressed in the following form

$$\text{minimize} \qquad f_0(x) \tag{2.17}$$

$$\text{subject to} \qquad f_i(x) \leq 0, \qquad \forall i = 1, .., m, \tag{2.18}$$

$$a_i^T x = b_i, \qquad \forall i = 1, .., p, \tag{2.19}$$

where $a_i \in \mathbb{R}^n$ and $b_i \in \mathbb{R}$ are some constants, the objective $f_0(x)$ and constraint functions $f_i(x)$ are convex functions.

It is difficult to find an optimal solution of an optimization problem if it is not convex in general. For a convex optimization, the optimal solution can be directly determined by solving the KKT necessary optimal conditions. This is stated in the following theorem.

Theorem 1: The KKT necessary optimal conditions (2.10)-(2.14) are also sufficient conditions for a convex optimization problem.

Theorem 1 means that the points x^* and (λ^*, ν^*) that satisfy the KKT conditions are also primal and dual optimal solutions.

2.2 WMMSE Beamforming Technique

This section discuss the general Weighted Minimum Mean Square Error (WMMSE) beamforming algorithm to solve a general beamforming optimization problem for MIMO systems [1]. In particular, we will present the system model, problem statement and detailed algorithm development.

Consider a MIMO communication system with $\mathcal{K}$ transmitters (or base stations) each equipped with M_κ antennas, $\kappa = 1, .., \mathcal{K}$. Furthermore, it is assumed that there are $\mathcal{I}_\kappa$ users served by transmitter κ and the i^{th} user served by transmitter κ, denoted as i_κ, is equipped with N_{i_κ} antennas.

Then, the receive signal $\mathbf{y}_{i_\kappa} \in \mathbb{C}^{N_{i_\kappa} \times 1}$ at user i_κ is given as

$$\mathbf{y}_{i_\kappa} = \underbrace{\mathbf{H}_{i_\kappa \kappa} \mathbf{V}_{i_\kappa} \mathbf{s}_{i_\kappa}}_{\text{desired signal}} + \underbrace{\sum_{m=1, m \neq i}^{\mathcal{I}_\kappa} \mathbf{H}_{i_\kappa \kappa} \mathbf{V}_{m_\kappa} \mathbf{s}_{m_\kappa}}_{\text{intracell interference}} + \underbrace{\sum_{\zeta=1, \zeta \neq \kappa}^{\mathcal{K}} \sum_{l=1}^{\mathcal{I}_\zeta} \mathbf{H}_{i_\kappa \zeta} \mathbf{V}_{l_\zeta} \mathbf{s}_{l_\zeta} + \mathbf{n}_{i_\kappa}}_{\text{intercell interference plus noise}}, \tag{2.20}$$

where $\mathbf{H}_{i_\kappa \zeta} \in \mathbb{C}^{N_{i_\kappa} \times M_\zeta}$ denotes the channel from transmitter ζ to receiver i_κ, $\mathbf{n}_{i_\kappa} \in \mathbb{C}^{N_{i_\kappa} \times 1}$ denotes the AWGN noise with distribution $\mathcal{CN}(0, \sigma_{i_\kappa}^2 \mathbf{I})$, $\mathbf{s}_{i_\kappa} \in \mathbb{C}^{d_{i_\kappa} \times 1}$ is the desired signal of user i_κ with expected value $\mathbb{E}(\mathbf{s}_{i_\kappa} \mathbf{s}_{i_\kappa}^H) = \mathbf{I}$, $\mathbf{I}$ is the identity matrix, and $\mathbf{V}_{i_\kappa} \in \mathbb{C}^{M_{i_\kappa} \times d_{i_\kappa}}$ denotes the beamformer. Hence, the data rate of user i_κ can be expressed as

$$R_{i_\kappa} = \log\det \left(\mathbf{I} + \mathbf{H}_{i_\kappa \kappa} \mathbf{V}_{i_\kappa} \mathbf{V}_{i_\kappa}^H \mathbf{H}_{i_\kappa \kappa}^H \left(\sum_{(l,\zeta) \neq (i,\kappa)} \mathbf{H}_{i_\kappa \zeta} \mathbf{V}_{l_\zeta} \mathbf{V}_{l_\zeta}^H \mathbf{H}_{i_\kappa \zeta}^H + \sigma_{i_\kappa}^2 \mathbf{I} \right)^{-1} \right). \tag{2.21}$$

Suppose that we are interested in solving a general sum utility maximization problem which can be stated as

$$\underset{\mathbf{V}}{\text{maximize}} \quad \sum_{\kappa=1}^{\mathcal{K}} \sum_{i_\kappa=1}^{\mathcal{I}_\kappa} u_{i_\kappa}(R_{i_\kappa}) \tag{2.22}$$

$$\text{subject to} \quad \sum_{i=1}^{\mathcal{I}_\kappa} \mathrm{Tr}(\mathbf{V}_{i_\kappa} \mathbf{V}_{i_\kappa}^H) \leq P_\kappa, \ \forall \kappa = 1, .., \mathcal{K}, \tag{2.23}$$

where P_κ denotes the maximum power of transmitter κ and $u_{i_\kappa}(.)$ represents the utility, which can be designed to capture desirable design goals such as balancing between throughput and fairness.

In [1], the authors prove the following relation between R_{i_κ} and mean square error covariance matrix $\mathbf{E}_{i_\kappa}^{\text{mmse}}$

$$R_{i_\kappa} = \log\,\det\left(\left(\,\mathbf{E}_{i_\kappa}^{\text{mmse}}\right)^{-1}\right), \tag{2.24}$$

where $\mathbf{E}_{i_\kappa}$ is given as

$$\mathbf{E}_{i_\kappa} = \mathbb{E}\left[\left(\hat{\mathbf{s}}_{i_\kappa} - \mathbf{s}_{i_\kappa}\right)\left(\hat{\mathbf{s}}_{i_\kappa} - \mathbf{s}_{i_\kappa}\right)^H\right], \tag{2.25}$$

and $\hat{\mathbf{s}}_{i_\kappa} = \mathbf{U}_{i_\kappa}^H \mathbf{y}_{i_\kappa}$, $\mathbf{E}_{i_\kappa}^{\text{mmse}}$ is the value of $\mathbf{E}_{i_\kappa}$ when $\mathbf{U}_{i_\kappa}$ corresponds to an MMSE receiver, which can be expressed as

$$\mathbf{U}_{i_\kappa}^{\text{mmse}} = \left(\sum_{\zeta=1}^{\mathcal{K}} \sum_{l=1}^{\mathcal{I}_\zeta} \mathbf{H}_{i_\kappa \zeta} \mathbf{V}_{l_\zeta} \mathbf{V}_{l_\zeta}^H \mathbf{H}_{i_\kappa \zeta}^H + \sigma_{i_\kappa}^2 \mathbf{I}\right)^{-1} \mathbf{H}_{i_\kappa \kappa} \mathbf{V}_{i_\kappa}. \tag{2.26}$$

Therefore, the optimization problem (2.22)-(2.23) is equivalent to the following sum mean square error (sum-MSE) minimization problem

$$\underset{\mathbf{V},\mathbf{U}}{\text{minimize}} \qquad \sum_{\kappa=1}^{\mathcal{K}} \sum_{i_\kappa=1}^{\mathcal{I}_\kappa} c_{i_\kappa}(\mathbf{E}_{i_\kappa}) \tag{2.27}$$

$$\text{subject to} \qquad \sum_{i=1}^{\mathcal{I}_\kappa} \text{Tr}(\mathbf{V}_{i_\kappa} \mathbf{V}_{i_\kappa}^H) \leq P_\kappa,\ \forall \kappa = 1, .., \mathcal{K}, \tag{2.28}$$

where $c_{i_\kappa}(\mathbf{E}_{i_\kappa}) = u_{i_\kappa}(-\log\,\det(\mathbf{E}_{i_\kappa}))$.

To tackle this problem, we introduce a new optimization variable $\mathbf{W}$ and consider the following matrix weighted sum-MSE minimization problem

$$\underset{\mathbf{V},\mathbf{U},\mathbf{W}}{\text{minimize}} \qquad \sum_{\kappa=1}^{\mathcal{K}} \sum_{i_\kappa=1}^{\mathcal{I}_\kappa} \left(\text{Tr}\left(\mathbf{W}_{i_\kappa}^H \mathbf{E}_{i_\kappa}\right) + c_{i_\kappa}\left(\boldsymbol{\gamma}_{i_\kappa}\left(\mathbf{W}_{i_\kappa}\right)\right) - \text{Tr}\left(\mathbf{W}_{i_\kappa}^H \boldsymbol{\gamma}_{i_\kappa}\left(\mathbf{W}_{i_\kappa}\right)\right)\right) \tag{2.29}$$

$$\text{subject to} \qquad \sum_{i=1}^{\mathcal{I}_\kappa} \text{Tr}(\mathbf{V}_{i_\kappa} \mathbf{V}_{i_\kappa}^H) \leq P_\kappa,\ \forall \kappa = 1, .., \mathcal{K}, \tag{2.30}$$

where $\boldsymbol{\gamma}_{i_\kappa} : \mathbb{R}^{d_{i_\kappa} \times d_{i_\kappa}} \to \mathbb{R}^{d_{i_\kappa} \times d_{i_\kappa}}$ is the inverse mapping of the gradient map $\nabla c_{i_\kappa}(\mathbf{E}_{i_\kappa})$. We now state an important result, which establishes the relationship between problems (2.22)-(2.23) and (2.29)-(2.30).

Theorem 2: If c_{i_κ} is strictly concave function, and for any fixed beamformers $\{\mathbf{V}, \mathbf{U}\}$, the the sum-utility maximization (2.22)-(2.23) is equivalent to the matrix weighted sum MSE minimization (2.29)-(2.30) and they have the same optimal solution.

Proof: For brevity, the subscript i_κ is neglected. To prove *Theorem 2*, we define

$$g(\mathbf{W}) = c\left(\boldsymbol{\gamma}\left(\mathbf{W}\right)\right) - \text{Tr}\left(\mathbf{W}^H \boldsymbol{\gamma}\left(\mathbf{W}\right)\right). \tag{2.31}$$

Then, the gradient of $g(\mathbf{W})$ can be computed as

$$\begin{aligned}
\nabla g(\mathbf{W}) &= \sum_{i,j} \frac{\partial c}{\partial \boldsymbol{\gamma}_{\boldsymbol{i,j}}} \nabla \boldsymbol{\gamma}_{i,j}(\mathbf{W}) - \nabla_{\mathbf{W}} \left(\sum_{i,j} \mathbf{W}_{i,j} \boldsymbol{\gamma}_{i,j}(\mathbf{W}) \right) \\
&= \sum_{i,j} \mathbf{W}_{i,j} \nabla \boldsymbol{\gamma}_{i,j}(\mathbf{W}) - \sum_{i,j} \mathbf{1}_{i,j} \boldsymbol{\gamma}_{\boldsymbol{i,j}}(\mathbf{W}) - \sum_{i,j} \mathbf{W}_{i,j} \nabla \boldsymbol{\gamma}_{i,j}(\mathbf{W}) \\
&= -\boldsymbol{\gamma}(\mathbf{W}),
\end{aligned} \tag{2.32}$$

where $\mathbf{W}_{i,j}$ denotes (i,j) element of matrix $\mathbf{W}$ and $\mathbf{1}_{i,j}$ denotes an all zero matrix except that the $(i,j)^{\text{th}}$ element is equal to 1.

Further, by defining $q(t, \mathbf{W}, \mathbf{Z}) = g(\mathbf{W} + t\mathbf{Z})$ for some feasible $\mathbf{Z}$, we have the following

$$\begin{aligned}
q(t_2, \mathbf{W}, \mathbf{Z}) &= c(\boldsymbol{\gamma}(\mathbf{W} + \boldsymbol{t_2}\mathbf{Z})) - \mathrm{Tr}((\mathbf{W} + t_2\mathbf{Z})^H \boldsymbol{\gamma}(\mathbf{W} + t_2\mathbf{Z})) \\
&> c(\boldsymbol{\gamma}(\mathbf{W} + t_1\mathbf{Z})) - \mathrm{Tr}((\mathbf{W} + t_1\mathbf{Z})^H \boldsymbol{\gamma}(\mathbf{W} + t_1\mathbf{Z})) - (t_2 - t_1)\mathrm{Tr}(\mathbf{Z}^H \boldsymbol{\gamma}(\mathbf{W} + t_1\mathbf{Z}))) \\
&= g(\mathbf{W} + t_1\mathbf{Z}) + \mathrm{Tr}(\mathbf{Z}^H \nabla g(\mathbf{W} + t_1\mathbf{Z}))(t_2 - t_1) \\
&= q(t_1, \mathbf{W}, \mathbf{Z}) + q'(t_1, \mathbf{W}, \mathbf{Z})(t_2 - t_1).
\end{aligned} \tag{2.33}$$

Thus, g is also a convex function. Hence, the objective function (2.29) is convex with respect to $\mathbf{W}$. Consequently, utilizing (2.32), the optimal value $\mathbf{W}^*$ is given as $\mathbf{W}^*_{i_\kappa} = \nabla c_{i_\kappa}(\mathbf{E}_{i_\kappa})$ or $\mathbf{E}_{i_\kappa} = \boldsymbol{\gamma}_{i_\kappa}(\mathbf{W}^*_{i_\kappa})$. By plugging this optimal value of $\mathbf{W}$ into (2.29), the equivalence of problem (2.29)-(2.30) and (2.22)-(2.23) can be established. ■

Therefore, it is sufficient to solve problem (2.29)-(2.30). For this problem, it can be verified that if we fix the two sets of variables $\{\mathbf{V}\}, \{\mathbf{U}\}, \{\mathbf{W}\}$, then the resulting optimization problem is convex with respect to the remaining variables. Hence, an iteration procedure can be developed to find these remaining variables as we fix two sets of other variables. Such a general WMMSE beamforming algorithm to solve the underlying utility optimization problem is described in details in Algorithm 6.

2.3 Proportional Fair User Scheduling

In this section, we present the proportional fair user scheduling scheme given in [3]. Let us consider a communication system with $\mathcal{K}$ transmitters (or cells), $\mathcal{S}$ sectors per cell, each transmitter serves $\tilde{N}_\kappa$ users per sector, and there are N carriers. Moreover, assume that each transmitter is equipped with M_κ antennas and each user is equipped N_u antennas. Then, the signal to interference plus noise ratio (SINR) of user i in sector ι served by transmitter κ on carrier n is given as

$$\mathsf{SINR}^n_{\kappa\iota bi} = \frac{p^n_{\kappa\iota i} |\left(\mathbf{u}^n_{\kappa\iota i}\right)^H \mathbf{H}^n_{\kappa\iota i,\kappa\iota} \mathbf{v}^n_{\kappa\iota b}|^2}{\sigma^2 + \sum\limits_{(\zeta,\tau,\varepsilon)\neq(\kappa,\iota,b)} p^n_{\zeta\tau\varepsilon} |\left(\mathbf{u}^n_{\kappa\iota i}\right)^H \mathbf{H}^n_{\kappa\iota i,\zeta\tau} \mathbf{v}^n_{\zeta\tau\varepsilon}|^2}, \tag{2.34}$$

Algorithm 6 **General WMMSE Beamforming Algorithm for MIMO systems**

Input: Initial choice transmit beamformers $\mathbf{V}_{i_\kappa}$'s such that $\mathsf{Tr}\{\mathbf{V}_{i_\kappa}\mathbf{V}_{i_\kappa}^H\} = \frac{P_\kappa}{i_\kappa}$.
Output: Transmit beamformer $\mathbf{V}_{i_\kappa}$'s.
Initialize: $\mathbf{V}_{i_\kappa}$'s.
while 1 **do**
    Set: $\mathbf{W}_{i_\kappa}^{'} = \mathbf{W}_{i_\kappa}$.
    Compute: $\mathbf{U}_{i_\kappa}$ as in (2.26).
    Compute: $\mathbf{W}_{i_\kappa} = \nabla c_{i_\kappa}\left(\mathbf{E}_{i_\kappa}\right)$.
    Compute: $\mathbf{V}_{l_\kappa}$ by solving (2.29)-(2.30) which is convex with respect to $\mathbf{V}$ when $\mathbf{U}, \mathbf{W}$ are fixed.
    if: $\left|\sum_{\zeta,l} \log\det\left(\mathbf{W}_{i_\kappa}\right) - \sum_{\zeta,l}\log\det\left(\mathbf{W}_{i_\kappa}^{'}\right)\right| < \epsilon$.
    break.
    end
end while

where $\mathbf{H}_{\kappa\iota i,\zeta\tau}^{n}$ denotes the channel gain matrix from transmitter ζ, sector τ to i^{th} user in cell κ, sector ι on carrier n, σ^2 denotes the noise power, $\mathbf{u}$, $\mathbf{v}$ denote the receive and transmit beamformers, respectively, and b denotes the b^{th} beamformer. Assuming that channel gain matrix, noise power, transmit power, transmit and receive beamformer are known, the scheduling problem aims to determine the user scheduling function $f(\kappa, \iota, b, n)$ returning the scheduled user that maximizes the sum logarithm utility as follows:

$$\underset{f}{\text{maximize}} \qquad \sum_{\kappa,\iota,i} \log\left(\bar{R}_{\kappa\iota i}\right), \tag{2.35}$$

where $\bar{R}_{\kappa\iota i} = \alpha\bar{R}_{\kappa\iota i} + (1-\alpha)R_{\kappa\iota i}$ is the long term average rate for a small value of α, the instantaneous rate $R_{\kappa\iota i} = \sum\limits_{(b,n):i=f(\kappa,\iota,b,n)} \log\left(1 + \mathsf{SINR}_{\kappa\iota b i}^{n}\right)$ and α is a constant in $(0,1)$.

The user scheduling function/decision to optimize the sum logarithm function, which guarantees the so-called proportional fairness, can be expressed as [3]

$$f(\kappa,\iota,b,n) = \text{argmax}_i \, \frac{\tilde{r}_{\kappa\iota b i}^{n}}{\bar{R}_{\kappa\iota i}}, \tag{2.36}$$

where $\tilde{r}_{\kappa\iota b i}^{n}$ denotes the instantaneous rate of user (κ, ι, i) on carrier n when it adopts beamformer b. The intuition behind (2.36) is that the user benefits the most from being assigned beamformer b on carrier n according the rate-ratio criterion must be scheduled. Furthermore, the scheduling decision given in (2.36) maximizes the objective (2.35) since the derivative of objective function (2.35) is $1/\bar{R}_{\kappa\iota i}$ [3].

Chapter 3

Resource Allocation for Multibeam MISO Satellite Systems

This chapter addresses the two resource allocation problems which aim at maximizing the system sum rate and sum utility of all users, respectively for a multibeam multiple input and single output (MISO) satellite communication system. We present two different resource allocation algorithms to solve the considered problems, namely the max sum rate algorithm (MSRA) and max utility algorithm (MUA), respectively and evaluate their performance via numerical studies.

3.1 System Model and Problem Formulation

3.1.1 System Model

We consider the downlink of a multibeam satellite system where the number of antenna feeds is J and there is a single antenna feed per beam. The beams are characterized by different planes with the corresponding 3 dB beamwidth defined by the solid angle where the gain at the edge is fallen by 3 dB with respect to the maximum gain. Therefore, the beam created by each antenna feed corresponds to an area with the border defining the 3dB gain contour. The satellite is assumed to be equipped with J antennas and each user has a single antenna. The problem of interest is to optimize the allocation of the transmit beamfomer and user set selection for each carrier so that underlying design objectives are maximized.

We denote P_{tot} as the total power of the satellite, N as the number of carriers, J as the number of beams. Moreover, we assume that there are K single-antenna users in the system, and we denote S_j as the set of users in beam j. Hence, we have $\sum_{j=1}^{J} |S_j| = K$. The data symbol transmitted to user i is denoted by s_i where the average power of s_i is given by $\mathbb{E}(s_i^2) = 1$ and its beamforming vector is $\mathbf{w}_{i,n}$. Let $\mathbf{h}_{i,n}$ be the channel gain from the satellite to user i on carrier n. Also, we introduce binary optimization variables to capture user scheduling decisions where $a_{i,n}$ is equal to 1 if user i is served by the satellite on carrier n, and it is 0, otherwise.

The received signal at user i on carrier n can be expressed as

$$r_{i,n} = a_{i,n}\mathbf{h}_{i,n}\mathbf{w}_{i,n}s_i + \sum_{k\neq i} a_{k,n}\mathbf{h}_{i,n}\mathbf{w}_{k,n}s_k + \eta_{i,n}, \forall i = 1,..,K, \tag{3.1}$$

where $\eta_{i,n}$ is the zero-mean Gaussian random noise with variance σ^2. The received signal to interference plus noise ratio (SINR) of user i on carrier n can be expressed as

$$\Gamma_{i,n} = \frac{a_{i,n}|\mathbf{h}_{i,n}\mathbf{w}_{i,n}|^2}{\sum_{k\neq i} a_{k,n}|\mathbf{h}_{i,n}\mathbf{w}_{k,n}|^2 + \sigma^2}. \tag{3.2}$$

Then, the achieved rate of user i on all allocated carriers is written as

$$R_i = \sum_{n=1}^{N} \log_2(1 + \Gamma_{i,n}), \tag{3.3}$$

and the system sum rate is given by

$$R = \sum_{i=1}^{K} R_i, \tag{3.4}$$

which is the total rate achieved by all users.

3.1.2 Problem Formulation

We consider two different design objectives, i.e., to maximize the system sum data rate and system sum utility. Both problems aim to optimize the beamformers and carrier allocation for users under the total satellite power constraint.

3.1.2.1 Max Sum Rate Problem (MSRP)

The MSRP problem can be formulated as

$$\underset{\{a_{i,n}\},\{\mathbf{w}_{i,n}\}}{\text{maximize}} \quad R \tag{3.5}$$

$$\text{subject to} \quad \sum_{i=1}^{K}\sum_{n=1}^{N} a_{i,n}\mathbf{w}_{i,n}^H\mathbf{w}_{i,n} \leqslant P_{tot}, \tag{3.6}$$

where (3.6) captures the constraint on the maximum satellite power.

3.1.2.2 Max Utility Problem (MUP)

The MUP problem can be formulated as

$$\underset{\{a_{i,n}\},\{\mathbf{w}_{i,n}\}}{\text{maximize}} \quad u_{\mathsf{tot}} \tag{3.7}$$

$$\text{subject to} \quad \sum_{i=1}^{K}\sum_{n=1}^{N} a_{i,n}\mathbf{w}_{i,n}^H\mathbf{w}_{i,n} \leqslant P_{tot}, \tag{3.8}$$

where the sum utility u_{tot} is given as

$$u_{\mathsf{tot}} = \sum_{i=1}^{K} u_i(\overline{R}_i) = \sum_{i=1}^{K} \log_2(\overline{R}_i). \tag{3.9}$$

Here, $\overline{R}_i$ is the long-term average rate of user i, which is updated exponentially as

$$\overline{R}_i(t+1) = \alpha\overline{R}_i(t) + (1-\alpha)R_i(t+1), \tag{3.10}$$

where $0 < \alpha < 1$ is a constant and $R_i(t)$ denotes the instantaneous rate of user i calculated from the fixed power spectrum allocation at time t.

3.2 Resource Allocation Algorithms

Both MSRP and MUP are mixed integer non-convex problems, which are difficult to solve. We, therefore, propose to decompose the beamforming and scheduling design tasks and iteratively update their solutions until convergence. Specifically, we will employ the WMMSE approach [1] to design for beamforming and develop appropriate scheduling algorithms to solve the two corresponding problems. For the developed iterative algorithms, beamforming design is conducted for a given scheduling (carrier assignment) solution and scheduling design exploits the beamforming solution in the previous iteration.

3.2.1 WMMSE Beamforming Algorithm

Beamforming is designed for each carrier which is assigned to the corresponding set of users (i.e., determined from the variables $a_{i,n}$). For brevity, we ignore the notations n and $a_{i,n}$ in the beamforming design. For a given user set selection for a considered carrier, the resource allocation problems can be expressed in the following general form:

$$\underset{\{\mathbf{w}_i\}}{\text{maximize}} \quad f(\mathbf{w}) \tag{3.11}$$

$$\text{subject to} \quad \sum_{i \in S} \mathbf{w}_i^H \mathbf{w}_i \leqslant P_{tot}, \tag{3.12}$$

where the function $f(.)$ corresponds to function $R(.)$ and $u_{\mathsf{tot}}(.)$ in the two considered problems, respectively and this optimization is conducted for the set of scheduled users S on carrier n.

We perform uniform power allocation over carriers; therefore, the maximum allocated power per carrier is P_{tot}/N. Then, problem (3.11)-(3.12) can be tackled by solving the following sum mean squared error (MSE) minimization problem [1]

$$\underset{\{\beta_i\},\{U_i\},\{\mathbf{w}_i\}}{\text{minimize}} \quad \sum_{i \in S} \{\beta_i^c E_i + c_i\left(\gamma_i\left(\beta_i\right)\right) - \beta_i^c\left(\gamma_i\left(\beta_i\right)\right)\} \tag{3.13}$$

$$\text{subject to} \quad \sum_{i \in S} \mathbf{w}_i^H \mathbf{w}_i \leqslant \frac{P_{tot}}{N}, \tag{3.14}$$

where E_i is the MSE, which is defined as

$$E_i = \mathbb{E}\left\{\left(\hat{r}_i - r_i\right)\left(\hat{r}_i - r_i\right)^c\right\}, \tag{3.15}$$

where $\mathbb{E}$ denotes the expectation, $\hat{r}_i = U_i^c r_i$ and U_i denotes the receiver (RX) detection weight; $(x)^c$ denotes the conjugate of x. Moreover, γ_i is the inverse mapping of the gradient map $\nabla c_i\left(E_i\right)$ and β_i is a weight parameter; $c_i(E_i)$ is the cost function defined as $c_i(E_i) = -u_i\left(-\log_2(E_i)\right)$. Note that for the sum rate maximization problem, we have $u_i = R_i$.

To solve problem (3.13), we fix two of three sets of variables $\{\beta_i\}, \{U_i\}, \{\mathbf{w}_i\}$ and compute the third one. The following iterative updates are employed to calculate these variables. We update RX weight parameter U_i by using MMSE receiver

$$U_i = \left(\sum_{l \in S} \mathbf{h}_i \mathbf{w}_l \mathbf{w}_l^H \mathbf{h}_i^H + \sigma^2\right)^{-1} \mathbf{h}_i \mathbf{w}_i, \forall i \in S. \tag{3.16}$$

The weight parameter β_i is updated by using the first order optimality condition for β_i as follows:

For Max Sum Rate Problem:

$$\beta_i = \left(1 - U_i^c \mathbf{h}_i \mathbf{w}_i\right)^{-1}, \forall i \in S. \tag{3.17}$$

For Max Utility Problem:

$$\beta_i = \frac{\left(1-\alpha\right) E_i^{-1}}{\left(\alpha \bar{R}_i + \left(1-\alpha\right) \log_2(E_i^{-1})\right)}, \forall i \in S. \tag{3.18}$$

Moreover, we update the transmit beamformer $\mathbf{w}_i$ from the first order optimality condition as follows:

$$\mathbf{w}_i = \left(\sum_{l \in S} \mathbf{h}_l^H U_l \beta_l U_l^c \mathbf{h}_l + \mu_i^* \mathbf{I}\right)^{-1} \mathbf{h}_i^H U_i \beta_i, \forall i \in S, \tag{3.19}$$

where $\mu_i^* \geq 0$ is the Lagrange multiplier, which can be computed as described in [1], and $\mathbf{I}$ is the identity matrix. The WMMSE beamforming algorithm is summarized in Algorithm 7. Given this beamforming design, we will develop the scheduling strategy and overall algorithms to solve MSRP and MUP in the following sections.

3.2.2 Max Sum Rate Algorithm (MSRA)

With the presented WMMSE-based beamforming design, we can calculate the beamforming solution and, therefore, the corresponding rates achieved by users scheduled on the same carrier. Based on this observation, we develop a greedy user scheduling algorithm for each carrier (we ignore the carrier index for brevity) where we sequentially choose the "best" user to add to the scheduling set over iterations.

Algorithm 7 WMMSE Beamforming Algorithm

Input: Initial choice transmit beamformers $\mathbf{w}_i$'s such that $\mathsf{Tr}\{\mathbf{w}_i\mathbf{w}_i^H\} = \frac{P_{tot}}{N.J}$.
Output: Transmit beamformer $\mathbf{w}_i$'s.
Initialize: $\mathbf{w}_i$'s
while 1 **do**
    Set: $\beta_i^{'} = \beta_i$.
    Compute: $U_i = \left(\sum_{l\in S} \mathbf{h}_i\mathbf{w}_l\mathbf{w}_l^H\mathbf{h}_i^H + \sigma^2\right)^{-1}\mathbf{h}_i\mathbf{w}_i, \forall i \in S.$
    Compute: $\beta_i = \left(1 - U_i^c\mathbf{h}_i\mathbf{w}_i\right)^{-1}, \forall i \in S$ for MSRP
    and $\beta_i = \frac{(1-\alpha)E_i^{-1}}{\left(\alpha\bar{R}_i+(1-\alpha)\log_2(E_i^{-1})\right)}, \forall i \in S$ for MUP.
    Compute: $\mathbf{w}_i = \left(\sum_{l\in S} \mathbf{h}_l^H U_l\beta_l U_l^c\mathbf{h}_l + \mu_i^*\mathbf{I}\right)^{-1}\mathbf{h}_i^H U_i\beta_i, \forall i \in S.$
    if: $|\sum_{i\in S}\log(\beta_i) - \sum_{i\in S}\log\left(\beta_i^{'}\right)| < \epsilon$.
    break.
    end
end while

For further explanation of the algorithm, let $i_1, i_2, i_3, \dots$ denote the user chosen in the first, second, third, ...iterations. Moreover, let $R_{i_1}, \forall i_1 = 1, .., K$ be the rate achieved by user i_1. Then, the "best" user i_1^* in the first iteration is the one that achieves the maximum rate, i.e.,

$$i_1^* = \underset{i_1}{\text{argmax}}\{R_{i_1}\}. \tag{3.20}$$

With the chosen user i_1^*, which is assumed to belong to beam j_1, we add one more user i_2, $i_2 \in \{1, .., J\}\backslash\{j_1\}$ in one of the remaining beams to form the subset $\{i_1^*, i_2\}$ (we schedule only one user per beam on each carrier to avoid strong interference). Note that we can compute the sum rate of the system with two users after running the presented WMMSE beamforming algorithm, denoted by $R_{i_1^*,i_2}$. We choose the second user i_2^*, which belongs to beam j_2, as follows:

$$i_2^* = \underset{i_2}{\text{argmax}}\{R_{i_1^*,i_2}\}. \tag{3.21}$$

Then, with the set $\{i_1^*, i_2^*\}$, we add one user i_3, $i_3 \in \{1, .., J\}\backslash\{j_1, j_2\}$ in one of the remaining beams to form the subset $\{i_1^*, i_2^*, i_3\}$ based on the achieved sum rate $R_{i_1^*,i_2^*,i_3}$ similarly

$$i_3^* = \underset{i_3}{\text{argmax}}\{R_{i_1^*,i_2^*,i_3}\}. \tag{3.22}$$

We can continue this process to search and add the 4-th, 5-th,... users until we find one user for each beam. This algorithm is described in Algorithm 8.

3.2.3 Max Utility Algorithm (MUA)

We propose an iterative algorithm, called Max Utility Algorithm (MUA), where we perform the following beamforming and scheduling tasks in the corresponding two steps as follows.

Algorithm 8 Max Sum Rate Algorithm (MSRA)

1: **Input:** Group size $G = 1$, satellite channel gains
2: **Output:** Scheduled set of users for each carrier and beamformers
3: **Initialize:** Group size $G = 1$
4: **while** $G \leqslant J$ **do**
5: **Find :** user i_G^* that satisfies

$$i_G^* = \underset{i_G}{\operatorname{argmax}}\{R_{i_1^*, i_2^* .., i_G}\}, \forall i_G \in J \backslash \{j_1, j_2, .., j_{G-1}\} \tag{3.23}$$

where $R_{i_1^*, i_2^* .., i_G}$ is the system sum rate for user set $i_1^*, i_2^* .., i_G$ calculated by using **Algorithm 7**.
6: **Set:** $G = G + 1$.
7: **end while**

1. **Step 1:** Beamformers are found by solving the Max Utility Problem for a given scheduled user set on each carrier n (given $a_{i,n}$ obtained in the previous iteration) as follows:

$$\underset{\{\mathbf{w}_{i,n}\}}{\text{maximize}} \quad u_{\mathsf{tot}} \tag{3.24}$$

$$\text{subject to} \quad \sum_{i \in S} a_{i,n} \mathbf{w}_{i,n}^H \mathbf{w}_{i,n} \leqslant \frac{P_{tot}}{N}, \tag{3.25}$$

   where the user scheduled set for the underlying carrier n is $S \subset \{1, .., K\}$ where $a_{i,n} = 1$ if $i \in S$. We then apply the WMMSE beamforming algorithm to determine beamforming vectors $\mathbf{w}_{i,n}$.

2. **Step 2:** We assume that in each beam and each carrier, there will be one user served by the satellite. Hence, the number of beamformers for every carrier is equal to the number of beams.

   With the beamformer designed in step 1, for the b-th beamformer vector $b = \{1, .., J\}$, we find user i^*, $i^* \in S_j$, to be scheduled in beam $j \in \{1, .., K\}$ as follows:

$$a_{i^*,n} = 1 \Leftrightarrow i^* = \underset{i \in S_j}{\operatorname{argmax}}\{\frac{\tilde{R}_{ib}}{\overline{R}_i}\}, \tag{3.26}$$

   where $\tilde{R}_{ib}$ is the rate achieved by user i when it is served by beamformer b and average rate $\overline{R}_i$ is updated as in (3.10).

This proposed strategy is summarized in Algorithm 9.

3.3 Numerical Results

For simulation, we consider a satellite system with three beams and there are two users per beam. The system parameters used in the simulations are summarized in Table 3.1 unless

Algorithm 9 Max Utility Algorithm (MUA)

1: **Input:** Initial choice of scheduled users, maximum number of iteration T_{max}, satellite channel gains
2: **Output:** Scheduled set of users for each carrier and beamformers
3: **Initialize:** iteration $t = 1$, initial scheduled users are chosen randomly.
4: **while** $t < T_{\mathsf{max}}$ **do**
5: **Compute:** beamformers by using **Algorithm 7**
6: **For each beamformer of each beam, find:** user i^* that satisfies

$$i^* = \underset{i \in S_j}{\operatorname{argmax}} \{ \frac{\tilde{R}_{ib}}{\overline{R}_i} \}. \tag{3.27}$$

7: **Update:** Chosen user set for considered carrier and average rates $\overline{R}_i$.
8: **Set:** $t = t + 1$.
9: **end while**

stated otherwise. We adopt the satellite channel model in [2]. For problem MSRP, the initial set of users is chosen randomly while the initial values of beamformers in the WMMSE algorithm (Algorithm 7) are set according to the Zero-Forcing (ZF) beamformers where the number of users for each carrier is less than or equal the number of beams. Moreover, user power is equal to the total power (per carrier) divided by the number of users when the number of users is larger than the number of beams.

Fig 3.1 shows the variation of system utility versus iterations under the the proposed MUA algorithm and the algorithm of [3] (denoted by AlgRef7). This figure shows that both MUA and AlgRef7 indeed converge. Moreover, except for some initial iterations, the achieved utility increases over iterations before settling down a stable value. In addition, the achieved sum utility of our proposed MUA algorithm is much higher than that of AlgRef7 in [3], which confirms the superior performance of our design.

Table 3.1: Simulation System Parameters (Downlink)

Parameters	Value
Orbit	GEO
Number of beams	3
Number of carriers	5
Number of users per beam	2
Beam diameter	250km
$3dB$ angle	0.4^o
Rain fading mean	-2.6dB
Rain fading variance	1.63dB
FL free space loss	210dB
Noise variance	$\sigma^2 = 10^{-24}$
α	0.9

In Fig 3.2, we show the system sum rate versus the satellite power due to the proposed MSRA. To obtain these results, we choose 10 different random choices of initial scheduled sets of users and show the average value of the data rate through different simulation runs. We also show the results obtained from exhaustive search of the best scheduled user sets for the MSRP for benchmarking purposes. It can be seen that the sum rate due to our proposed MSRA is very close to that due to the exhaustive search, which confirms the efficiency of our algorithm. Note that our proposed MSRA is based on the greedy scheduling mechanism so it has much lower complexity than that due to the exhaustive search. Moreover, this figure illustrates that the sum rate of MUA is much lower than that due to MSRA. This is the price in terms of system sum rate one has to pay to attain more fairness in resource sharing for users as will be described shortly.

In Fig 3.3, we show the data rates of different users due to the proposed MSRA and MUA algorithms and corresponding fairness indices of the two algorithms where the satellite power is 50W. Here, we use the popular Jain's fairness index, which can be calculated as $F_I = \left(\sum_{i=1}^{K} R_i\right)^2 / \left(N.\sum_{i=1}^{K} R_i^2\right)$ [52]. The fairness index is larger if a resource allocation strategy provides fairer resource sharing and the maximum value of fairness index is 1. It can be seen that the MUA results in fairer rate distribution for different users compared to the MSRA. This is also confirmed by the fact that the fairness index of MUA is higher than that of MSRA (0.8581 versus 0.7199, respectively).

We illustrate the variations of fairness index of both proposed algorithms versus the number of users per beam in Fig 3.4. Again, this figure confirms that the MUA results in quite higher fairness index compared to the MSRA. Moreover, the fairness index of either algorithm decreases as the number of users per beam increases. This is because when we increase the number of

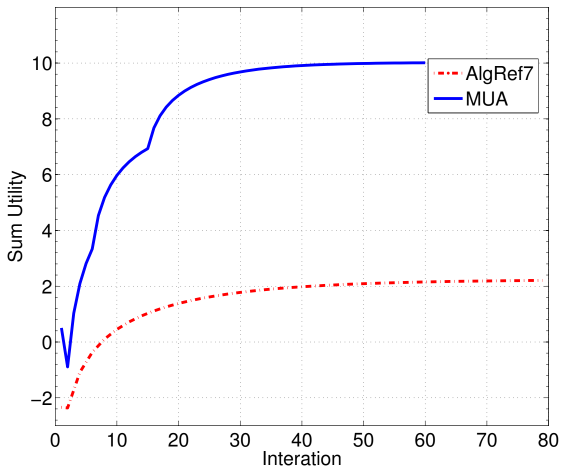

Figure 3.1: Convergence of Algorithm 9 (MUA) and the Algorithm in [3]

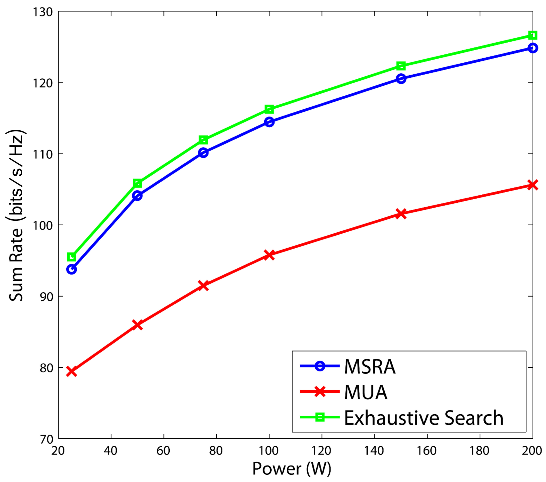

Figure 3.2: System sum rate versus satellite power

users in the system, it would be more difficult to achieve very fair rate sharing among all the users. It is also interesting that the fairness indices of the two proposed algorithms tend to be close to each other as the number of users per beam becomes sufficiently large.

Finally, we show the variations of system sum rate versus the number of carriers in Fig 3.5 for the satellite power of 25W and 35W. We can see that the sum rate increases as the number of carriers increases. This is expected since larger number of carriers means that there is more radio resources to be shared among the users. Moreover, this figure also reconfirms that the MSRA achieves higher sum rate than the MUA for all considered numbers of carriers.

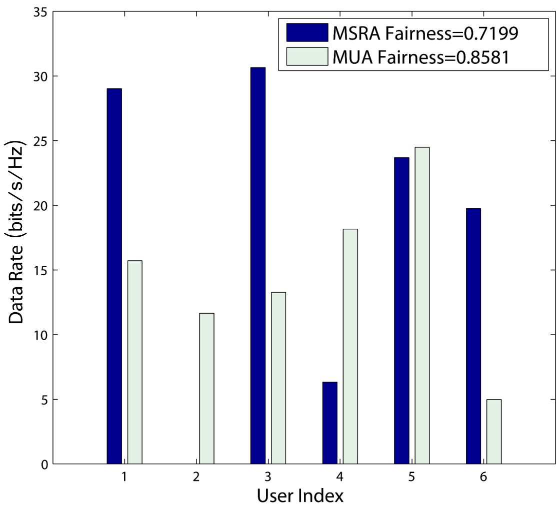

Figure 3.3: User rate distribution

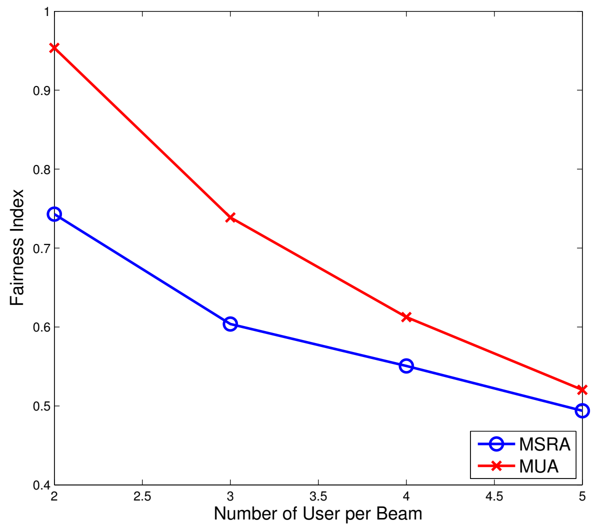

Figure 3.4: Fairness index versus number of users per beam

3.4 Conclusion

In this chapter, we have considered the resource allocation for the downlink multibeam MIMO satellite system where we have studied the sum rate and sum utility maximization problems. We have proposed two resource allocation algorithms to solve these problems, namely the Max Sum Rate Algorithm (MSRA) and Max Utility Algorithm (MUA). These two algorithms are based on the decomposed design where we have adopted the WMMSE approach for beamforming design and proposed novel scheduling strategies to optimize the two different objectives of the considered problems. Numerical results have shown that the MSRA can achieve higher data rate than MUA at the cost of lower fairness index. Moreover, the MSRA results in system sum rate, which is very close to that achieved by the exhaustive search of the scheduling solution. We

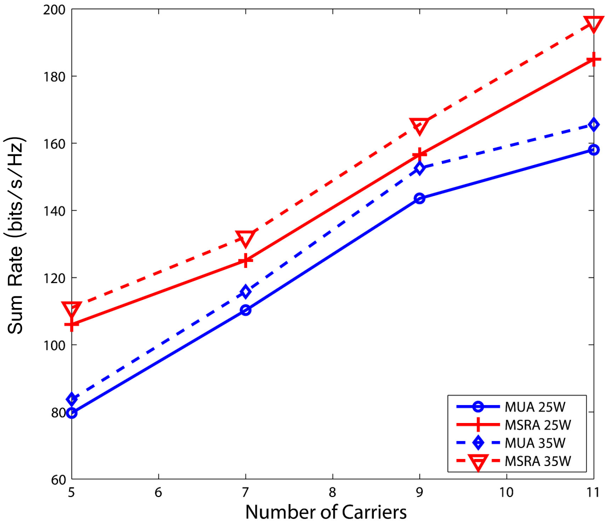

Figure 3.5: System sume rate versus number of carriers

have also presented the variations of system sum rates due to both proposed algorithms versus the number of users per beam and the number of carriers.

Chapter 4

Cognitive Radio Based Resource Allocation in Dual Satellite Systems

In this chapter, we present the resource allocation design for the uplink communications of the dual satellites operating on the same spectrum by using the cognitive radio concept where the two satellites are treated as the primary and secondary satellites, respectively. The design aims at maximizing the average sum rate which does not require the instantaneous CSI knowledge where the secondary satellite users' (SU) powers and angles toward the primary satellite are optimized subject to constraints on the maximum power and average interference at the primary satellite.

4.1 System Model and Problem Formulation

4.1.1 System Model

We consider the uplink communications of two satellites with overlapping service areas and frequency band where one is considered the primary satellite and the other is the secondary satellite. We assume that there are K secondary single-antenna satellite users and they share N licensed frequency carriers with the primary satellite under interference constraints to be specified soon. In this chapter, we study the resource allocation for secondary satellite users only. Moreover, we assume that each carrier can be allocated to at most one satellite user but one satellite user can utilize multiple carriers.

Let C_i denote the set of carriers allocated to the i^{th} satellite user and $p_{i,n}$ denotes the transmit power of i^{th} satellite user on carrier n, $n \in C_i$. Then, the SNR of i^{th} SU on carrier n can be written as

$$\Gamma_{i,n}^{\mathsf{UL}} = \frac{p_{i,n}\hat{b}_i\xi_{i,n}^{-1}G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2}, \tag{4.1}$$

where $\hat{b}_i = b_{max}b_i$, b_{max} and b_i represent the free space loss and secondary satellite beam gain, respectively [2], $G^{\mathsf{SU}}(\theta_i)$ denotes the antenna gain of satellite user, θ_i denotes the off axis angle

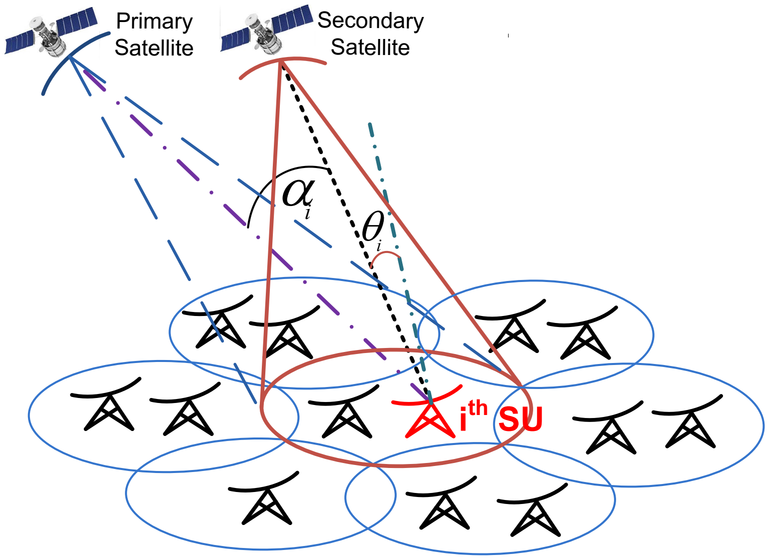

Figure 4.1: Dual Satellite System

from the boresight line which is illustrated in Fig 4.1, $\sigma_{i,n}^2$ denotes the noise power and $\xi_{i,n}$ is the rain attenuation between the i^{th} user and the secondary satellite which has the log normal distribution, i.e. $ln(\xi_{dB}) \sim \mathcal{N}(\mu, \hat{\sigma})$[2].

Then, the average data rate of the i^{th} satellite user on carrier n can be calculated as

$$\bar{R}_{i,n}^{\mathsf{UL}} = \int_{1}^{+\infty} W \log_2 \left(1 + \Gamma_{i,n}^{\mathsf{UL}}\right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n}, \tag{4.2}$$

where $f_{\Xi}(\xi_{i,n})$ denotes the pdf of rain attenuation, W denotes the bandwidth. The integral is computed from 1 because the rain attenuation $\xi_{i,n}$ is always larger than 1. Hence, the average sum rate of all satellite users can be written as

$$\bar{R}^{\mathsf{UL}} = \sum_{i,n \in C_i} \int_{1}^{+\infty} W \log_2 \left(1 + \Gamma_{i,n}^{\mathsf{UL}}\right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n}. \tag{4.3}$$

The interference caused by the i^{th} satellite user to the primary satellite on carrier n can be computed as

$$I_{i,n} = \frac{p_{i,n} \hat{b}_i^P G^{\mathsf{SU}}(\theta_i + \alpha_i)}{\xi_{i,n}^{\mathsf{P}}}, \tag{4.4}$$

where $\hat{b}_i^P = b_{max} b_i^{\mathsf{P}}$, b_i^P is the primary satellite beam gain, $\xi_{i,n}^{\mathsf{P}}$ is the rain attenuation between the i^{th} user and the primary satellite, and the angle seen from i^{th} user towards two satellites with overlapping coverage, denoted as α_i and shown in Fig 4.1. Thus, the average value of $I_{i,n}$ can be expressed as

$$\bar{I}_{i,n} = p_{i,n} \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) \int_{1}^{+\infty} \frac{f_{\Xi}(\xi_{i,n}^{\mathsf{P}})}{\xi_{i,n}^{\mathsf{P}}} d\xi_{i,n}^{\mathsf{P}}. \tag{4.5}$$

4.1.2 Problem Formulation

We consider the resource allocation for the cognitive satellite system where our design aims to maximize the average sum rate of the secondary satellite by optimizing the power allocation and angles of satellite users under the total satellite power constraints and per carrier average interference constraints at the primary satellite. This resource allocation problem can be stated as follows:

$$\underset{\{p_{i,n},\theta_i\}}{\text{maximize}} \quad \bar{R}^{\mathsf{UL}} \tag{4.6}$$

$$\text{subject to} \quad \bar{I}_{i,n} \leq \bar{I}_{i,n}^{\mathsf{TH}}, \forall i = 1,..,K, n \in C_i, \tag{4.7}$$

$$\sum_{n \in C_i} p_{i,n} \leq P_i^{max}, \forall i = 1,..,K, \tag{4.8}$$

$$p_{i,n} \geq 0, \forall i = 1,..,K, n \in C_i, \tag{4.9}$$

$$0 \leq \theta_i \leq \frac{\theta_{i3dB}}{2}, \forall i = 1,..,K, \tag{4.10}$$

where $\bar{I}_{i,n}^{\mathsf{TH}}$ denotes the interference threshold on carrier n for user i, P_i^{max} is the maximum power of satellite user i, and θ_{i3dB} is the 3dB angle of i^{th} satellite user's antenna. In this problem, (4.7) captures the per carrier average interference constraints, (4.8) and (4.9) denote the power constraints of satellite users, and (4.10) captures the angle constraints of satellite users.

4.2 Resource Allocation Algorithms

In order to solve problem (4.6)-(4.10), we propose an iterative algorithm where we sequentially optimize the power allocation and satellite users' angles in each iteration. Details of this proposed algorithm are presented in the following.

4.2.1 Power Allocation for Given Users' Angles

When the angles of satellite users are given, the studied optimization problem becomes the following power allocation problem

$$\underset{\{p_{i,n}\}}{\text{maximize}} \quad \sum_{i,n \in C_i} \int_1^{+\infty} W \log_2 \left(1 + \frac{p_{i,n} \hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2} \right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n} \tag{4.11}$$

$$\text{subject to} \quad a p_{i,n} \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) \leq \bar{I}_{i,n}^{\mathsf{TH}}, \forall i = 1,..,K, n \in C_i, \tag{4.12}$$

$$\sum_{n \in C_i} p_{i,n} \leq P_i^{max}, \forall i = 1,..,K, \tag{4.13}$$

$$p_{i,n} \geq 0, \forall i = 1,..,K, n \in C_i, \tag{4.14}$$

where a denotes the average satellite rain attenuation, which can be calculated as

$$a = \int_{1}^{+\infty} \frac{f_{\Xi}(\xi)}{\xi} d\xi. \tag{4.15}$$

Exploiting its decomposed structure, we can decompose problem (4.11) into the following K subproblems

$$\underset{\{p_{i,n}\}}{\text{maximize}} \quad \sum_{n \in C_i} \int_{1}^{+\infty} W \log_2 \left(1 + \frac{p_{i,n} \hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2}\right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n} \tag{4.16}$$

$$\text{subject to} \quad a p_{i,n} \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) \leq \bar{I}_{i,n}^{\mathsf{TH}}, \forall n \in C_i, \tag{4.17}$$

$$\sum_{n \in C_i} p_{i,n} \leq P_i^{max}, \tag{4.18}$$

$$p_{i,n} \geq 0, \forall n \in C_i. \tag{4.19}$$

Since the functions inside the intergrals of (4.16) are concave with respect to the transmit powers, so objective function of each sub-problem i is a concave function of the transmit powers. Furthermore, the constraints (4.17)-(4.19) are linear. Therefore, these sub-problems are convex optimization problems, which can be solved optimally by using the dual-based Lagrangian method.

Toward this end, the Lagrangian of problem (4.16) can be written as

$$\mathcal{L} = \sum_{n \in C_i} \int_{1}^{+\infty} W \log_2 \left(1 + \frac{p_{i,n} \hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2}\right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n} - \delta_i \left(\sum_{n \in C_i} p_{i,n} - P_i^{max}\right) - \sum_{n \in C_i} \lambda_{i,n} \left(a p_{i,n} \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) - \bar{I}_{i,n}^{\mathsf{TH}}\right), \tag{4.20}$$

where $\lambda_{i,n}$ and δ_i are Lagrange multipliers associated with the interference and power constraints, respectively.

Then, we study the Karush-Kuhn-Tucker optimality conditions for the optimal power allocation solution of (4.16) as follows:

$$\frac{\delta \mathcal{L}}{\delta p_{i,n}} = \int_{1}^{+\infty} W \frac{\hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\left(\sigma_{i,n}^2 + p_{i,n} \hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)\right) \ln 2} f_{\Xi}(\xi_{i,n}) d\xi_{i,n} - \delta_i - \lambda_{i,n} a \hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) = 0. \tag{4.21}$$

Since the function inside the integral of (4.21) is positive in the interval of integration. Moreover, this function decreases its value when $p_{i.n}$ is increased. Hence, the first term in (4.21) is a decreasing function of $p_{i,n}$. Therefore, for given values of the dual variables $\lambda_{i,n}$ and δ_i, we can solve (4.21) optimally by utilizing the bisection method.

Moreover, we can employ the standard sub-gradient method to iteratively update the dual variables toward their optimal values as follows:

$$\lambda_{i,n}(t+1) = \left[\lambda_{i,n}(t) + e_{i,n}\left(ap_{i,n}\hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) - \bar{I}_{i,n}^{\mathsf{TH}}\right)\right]^+, \tag{4.22}$$

$$\delta_i(t+1) = \left[\delta_i(t) + \bar{s}_i\left(\sum_{n\in C_i} p_{i,n} - P_i^{max}\right)\right]^+, \tag{4.23}$$

where $[x]^+ = \max(x, 0)$, t denotes the iteration index, $\bar{s}_i$ and $e_{i,n}$ are the step sizes.

The overall optimal power allocation algorithm is summarized in Algorithm 10. Because the power allocation problem (4.11)-(4.12) is convex, the proposed iteration primal-dual update based algorithm (i.e., Algorithm 10) converges to the global optimal solution of problem (4.11)-(4.12).

Algorithm 10 Power Allocation

1: **Input:** Initialize non-negative Lagrange multipliers $\lambda_{i,n}$'s and δ_i's randomly.
2: **Output:** Power allocation $p_{i,n}$.
3: Set iteration: $t = 1$.
4: **repeat**
5:     Update the power allocation $p_{i,n}$'s as the equation (4.21).
6:     Update the Lagrange multipliers $\lambda_{i,n}$'s and δ_i's as in (4.22) and (4.23), respectively.
7:     Update iteration index: $t = t + 1$.
8: **until** Convergence

4.2.2 Optimization of Satellite Users' Angles for Given Power Allocation Solution

For a given power allocation solution, the studied optimization problem becomes the following optimization problem

$$\underset{\{\theta_i\}}{\text{maximize}} \quad \sum_{i,n\in C_i} \int_1^{+\infty} W \log_2\left(1 + \frac{p_{i,n}\hat{b}_i \xi_{i,n}^{-1} G^{\mathsf{SU}}(\theta_i)}{\sigma_{i,n}^2}\right) f_{\Xi}(\xi_{i,n}) d\xi_{i,n} \tag{4.24}$$

$$\text{subject to} \quad ap_{i,n}\hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\theta_i + \alpha_i) \le \bar{I}_{i,n}^{\mathsf{TH}}, \forall i = 1, .., K, \forall n \in C_i, \tag{4.25}$$

$$0 \le \theta_i \le \frac{\theta_{i3dB}}{2}, \forall i = 1, .., K. \tag{4.26}$$

We assume that the antenna gain $G^{\mathsf{SU}}(\theta_i)$ is a decreasing function of θ_i. Then, it can be observed that both the objective function and the average interference (i.e., the left hand side of the interference constraints (4.25)) are decreasing with increasing user's angle θ_i. Hence, to achieve optimal value for (4.24), we simply need to determine the minimum value of θ_i while ensuring that the average interference constraints (4.25) can be maintained. With the optimal power allocation obtained by using Algorithm 1 and the optimal satellite users' angles obtained by solving (4.24)-(4.26), our proposed algorithm is summarized in Algorithm 11.

Algorithm 11 Average Sum Rate Maximization (ASRM)

1: **Input:** initialize θ_i's are chosen randomly.
2: **Output:** power allocation $p_{i,n}$ and users' angles θ_is.
3: Initial values of θ_i's are chosen randomly.
4: **for** every user in the system **do**
5:     **repeat**
6:         Update power allocation $p_{i,n}$'s using Algorithm 10.
7:         Update the satellite users' angles θ_i's by solving problem (4.24)-(4.26).
8:     **until** Convergence
9: **end for**

The convergence of this algorithm can be proved as follows. When θ_i's are given, Algorithm 10 can obtain the optimal solution of problem (4.11)-(4.14). Thus, average sum rate will be improved over iterations as one runs Algorithm 10. Moreover, for the obtained power allocation solution $p_{i,n}$'s in each iteration, the updates of the users' angles θ_i's in problem (4.24)-(4.26) will further improve this average sum rate. Hence, the objective function will monotonically increase over iterations. Therefore, Algorithm 11 converges and achieves at least local optimal solution.

4.3 Numerical Results

We consider a dual satellite system where the secondary satellite has seven beams, two users per beam and each secondary satellite user is allocated three carriers unless stated otherwise. We adopt the satellite channel model in [2] while the satellite user's antenna model is standardised gain patterns in ITU-R Recommendations which can be expressed as follows [53] (page 91)

$$G_{dBi}^{\mathsf{SU}} = \begin{cases} G_{dBi}^{max} - 12\left(\frac{\theta}{\theta_{3dB}}\right)^2 & , 0^\circ \leqslant \theta \leqslant \frac{\theta_{3dB}}{2}^\circ, \\ 29 - 25\log_{10}\theta & \text{if } 1.5^\circ \leqslant \theta \leqslant 7^\circ, \\ 8 & \text{if } 7^\circ < \theta \leqslant 9.2^\circ, \\ 32 - 25\log_{10}\theta & \text{if } 9.2^\circ < \theta \leqslant 48^\circ, \\ -10 & \text{if } 48^\circ < \theta \leqslant 85^\circ, \\ 0 & \text{if } 85^\circ < \theta \leqslant 180^\circ, \end{cases} \tag{4.27}$$

where G_{dBi}^{max} denotes maximum antenna gain. Note that we adopt the standardised gain patterns in ITU-R Recommendations FCC CFR 25.209 [54] which defines the pattern for earth stations operating in the 20/30 GHz band.

The interference threshold will be generated randomly in the interval $\left(0, I_{i,n}^{\mathsf{max}}\right)$, where $I_{i,n}^{\mathsf{max}} = P_i^{\mathsf{max}} G(\alpha_i) a\hat{b}_i^{\mathsf{P}}$ represents the maximum interference that user i can create to the primary satellite on carrier $n \in C_i$ with its maximum power P_i^{max}. The parameter setting for our simulation is summarized in Table 4.1. We assume that the angle from each user to the two satellite is equal to $\alpha_i = 4.2^\circ$ (as in the Anik-F3 and ViaSat-1 dual satellite system). For performance comparison with the proposed algorithm, we consider the following two schemes

- Fixed Zero Degree (FZD): for this scheme, the angle of any secondary satellite user i (i.e., θ_i) is always set equal to zero whereas the power allocation solution is determined by using Algorithm 10.

- Fixed Zero Degree and Uniform Power Allocation (FZDUPA): for this scheme, the angle of any secondary satellite user i (i.e., θ_i) is always set equal to zero whereas uniform power allocation is performed as follows:

$$p_{i,n} = \begin{cases} \frac{P_i^{max}}{|C_i|} & \text{if } \frac{P_i^{max}}{|C_i|} G^{\mathsf{SU}}(\alpha_i) < \frac{\bar{I}_{i,n}^{\mathsf{TH}}}{a\hat{b}_i^{\mathsf{P}}}, \forall n \in C_i \\ \min_{n \in C_i}\{\frac{\bar{I}_{i,n}^{\mathsf{TH}}}{a\hat{b}_i^{\mathsf{P}} G^{\mathsf{SU}}(\alpha_i)}\} & \text{if otherwise}, \end{cases} \tag{4.28}$$

The intuition behind zero degree angle is that the gain of user's antenna is maximum when we set the angle to zero.

The average SNR is defined as

$$\text{Average SNR} = \frac{a\hat{b}_i G(\alpha_i) P_i^{\mathsf{max}}/2}{\sigma_{i,n}^2}, \tag{4.29}$$

where a is the average satellite channel gain given in (4.15).

Table 4.1: Simulation System Parameters (Uplink)

Parameters	Value
Orbit	GEO
Earth's radius	6371km
Frequency	Ka Band
Number of beams	7
Number of carriers	3
Number of users per beam	2
Beam diameter	250km
Satellite $3dB$ angle	0.4^o
Rain Attenuation mean	-2.6dB
Rain Attenuation variance	1.63dB
FL free space loss	210dB
SU's reflector diameter	0.5m
SU's antenna efficiency	0.6
SU's maximum power	10W
Carrier bandwidth	16.6 MHz

Fig 4.2 shows the variation of average sum rate over iterations for the proposed ASRM algorithm under different values of users' maximum power. This figure confirms that our proposed algorithm indeed converges. Moreover, the achieved average sum rate increases over iterations before settling down a stable value. Also, the proposed algorithm converges after about six iterations, which is pretty fast.

In Table 4.2, we present the sum rate gains of the proposed ASRM algorithm with respect to the FZDUPA scheme in % for different values of secondary user's maximum power and number of carriers per secondary user. The results in this table confirms the significant sum rate gain, which is from 11.21% to 25.59%. Moreover, the sum rate gain tends to increase with the higher SU's maximum power. This could come from the fact that the proposed ASRM algorithm employs the optimal power allocation, which, therefore, better exploits the larger power resource as the SU's maximum power increases.

Table 4.2: Sum-Rate Improvement of ASRM w.r.t. FZDUPA (%)

		SU's Power (W)				
		10	12	14	16	18
Carriers Per User	3	14.65	15.56	19.86	21.34	22.32
	5	12.21	14.87	15.71	23.22	25.59
	7	11.21	14.75	19.29	19.91	21.47

In Fig 4.3, we show the average sum rate versus increment of interference threshold (IIT) where the IIT is defined as

$$\mathrm{IIT} = \frac{\bar{I}_{i,n}^{\mathsf{TH}} - \tilde{I}_{i,n}}{\min_i a\hat{b}_i^{\mathsf{P}}}, \tag{4.30}$$

where $\tilde{I}_{i,n}$'s are chosen randomly in $\left(0, I_{i,n}^{\mathsf{max}}\right)$, where $I_{i,n}^{\mathsf{max}} = P_i^{\mathsf{max}} G(\alpha_i) a\hat{b}_i^{\mathsf{P}}$ for each user and each carrier. Then, the average interference threshold $\bar{I}_{i,n}^{\mathsf{TH}}$ can be calculated based on $\tilde{I}_{i,n}$ and IIT. In our simulation, for a given value of IIT, each user and carrier will have the same IIT. We can see that the achieved average sum rate increases with the IIT (with the interference threshold as well). Furthermore, our proposed ASRM Alg. results in better average sum rate than those due to the FZD and FZDUPA schemes.

In Fig 4.4, we show the variations of average sum rate with the satellite users' maximum power due to the proposed ASRM algorithm as well as the FZD and FZDUPA schemes. As can be seen from this figure, the average sum rate obtained from ASRM algorithm is much higher than those due to the FZD and FZDUPA schemes. Moreover, the average sum rates obtained by the three schemes increase with the satellite users' maximum power before getting saturated at sufficiently large users' maximum power. This is because the average interference constraints at the primary satellite limit the allowable transmit powers from the satellite users.

Finally, Fig 4.5 demonstrates the average sum rate versus the number of users per beam. We consider the cases when each user is allocated with 3 and 7 carriers. It can be observed that the average sum rate increases with the number of users and carriers. This is expected since larger number of users and carriers results in larger power resource and carrier resource and enhanced system diversity. Moreover, the results in this figure also reconfirm that our proposed ASRM algorithm outperforms the FZD and FZDUPA schemes for the considered numbers of users.

4.4 Conclusion

In this chapter, we have studied the cognitive radio based resource allocation problem for the dual satellite system which aims to maximize the average sum rate of the secondary satellite subject to the satellite users' power constraints and per carrier average interference constraints of

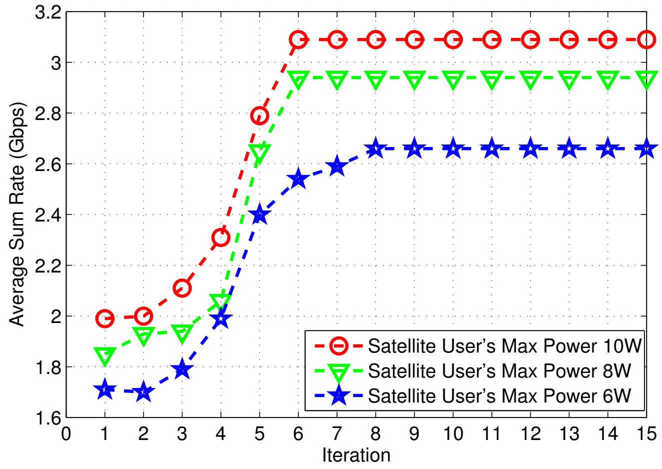

Figure 4.2: Convergence of ASRM alg. for K=14 users, J=7 beams, average SNR=15dB, $\bar{I}^{\mathsf{TH}}_{i,n}$'s are set randomly.

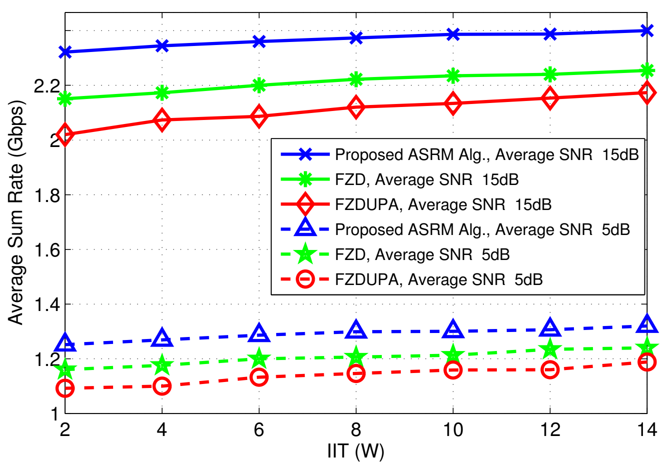

Figure 4.3: Average sum rate vs interference threshold increment for K=14 users, J=7 beams.

the primary satellite. We have proposed the Average Sum Rate Maximization (ASRM) algorithm to tackle this problem by iteratively updating the satellite users' power and their angles toward the primary satellite. Numerical results have confirmed the convergence of the proposed ASRM algorithm with increasing average sum rate over iterations. Moreover, we have showed that the ASRM algorithm achieves a substantial sum rate gain over the other conventional schemes.

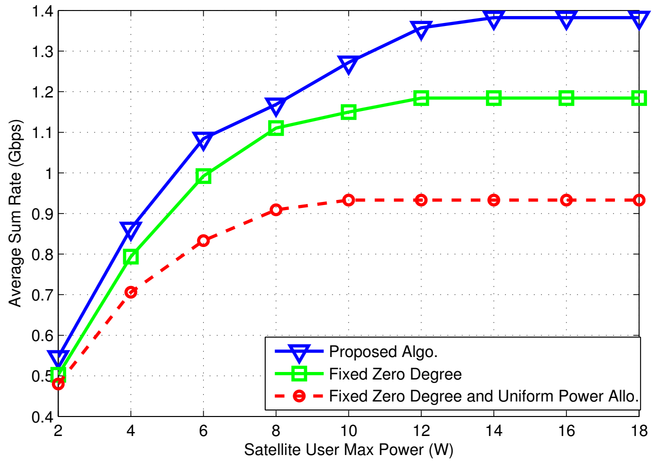

Figure 4.4: Average sum rate vs max power of satellite user for K=14, J=7, average SNR=15dB, $\bar{I}_{i,n}^{\mathsf{TH}}$'s are set randomly.

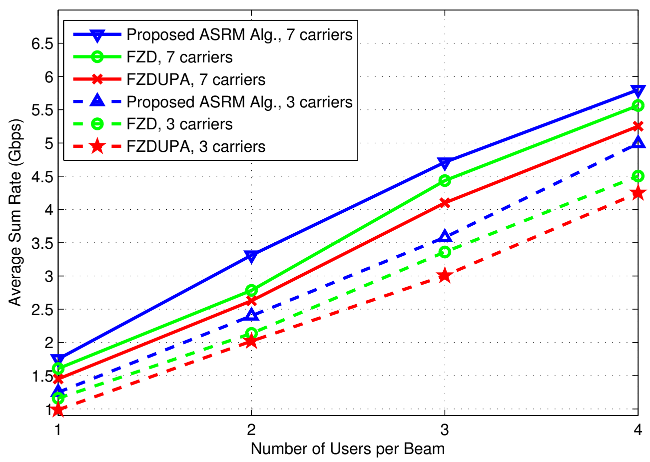

Figure 4.5: Average sum rate vs number of users per beam for J=7, average SNR=15dB, $\bar{I}_{i,n}^{\mathsf{TH}}$'s are set randomly.

Chapter 5

Conclusions and Future Work

5.1 Conclusion Remarks

In this thesis, we have developed some resource allocation algorithms for advanced radio resource management in satellite systems. The design has been conducted for two different scenarios, namely the single-satellite system and co-existing dual satellite system.

For the multibeam single-satellite system, we have addressed the joint downlink beamforming, carrier allocation and user scheduling problems of a multi-carrier multibeam satellite system which aim to maximize the system sum rate or sum utility. Then, we have devised two iteration algorithms, namely Max Sum Rate Algorithm (MSRA) and Max Utility Algorithm (MUA), to solve the two underlying problems. To evaluate the performance of the proposed algorithms, numerical studies have been conducted. Numerical results have shown that the MSRA algorithm can achieve up to 20% throughput gain compared to the MUA algorithm while the later attains fairer resource sharing for the users. Moreover, it has been shown that the gap in terms of fairness index between the two algorithms becomes smaller when the number of users per beam increases.

For the co-existing dual satellite system, we have proposed the cognitive radio based uplink resource allocation framework which maximizes the average system sum rate through optimizing the transmit powers and secondary users' angles while maintaining the interference constraints at the primary satellite. We have then conducted numerical studies for performance evaluation and comparison of the proposed algorithm and other conventional schemes. Numerical results have shown that the proposed algorithm can achieve about 10-20% sum rate gain compared conventional schemes with zero secondary users' angles and/or uniform power allocation. Moreover, impacts of different system parameters such as maximum user power, number of users per beam, and interference threshold on the sum rate performance have also been investigated.

5.2 Future Work

Even though the thesis has made some important contributions in the radio resource allocation for satellite systems, there are still several open research issues for further studies. We would like to discuss some potential directions which can be pursued in our future work.

1. Our research allocation studies have focused on maximization of the sum rate or sum utility for a single-satellite system. However, other important design objectives widely used in the terrestrial cellular context such as energy efficiency or total power can also be considered for radio resource management in the satellite systems. Moreover, the proposed algorithms can be improved by performing more effective power allocation for different carriers instead of the employed uniform power allocation strategy.

2. Our proposed resource allocation framework for the uplink dual satellite system must be implemented in the centralized manner. Development of an efficient distributed resource allocation algorithm for this setting is an important direction for further study.

3. There has been some initiative in applying the cloud radio access network (C-RAN) techniques to the satellite domain [55, 56], but this is still very under-explored in the current literature. Intelligent integration of the C-RAN techniques into satellite systems via suitable resource allocation models and algorithms deserve further study.

5.3 List of Publications

1. **D. Nguyen** and L.B. Le , "Resource allocation for multibeam MISO satellite systems: sum rate versus proportional fair optimization," in *Proc. IEEE Wireless Commun. and Networking Conf. (WCNC), Workshop on Commun. in Extreme Conditions*, Doha, Qatar, April 2016.

2. **D. Nguyen** and L.B. Le , "Cognitive radio based resource allocation for sum rate maximization in dual satellite systems," submitted.

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