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Allocation Dynamique De Ressources Pour Les Réseaux Cellulaires Sans Fil Full-duplex OFDMA

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Résumé

0.1 Motivation

Dans les systèmes de communication sans fil de prochaine génération, l'augmentation de la capacité du système est l'un des facteurs les plus importants à cause de la demande continuellement croissante en trafic de données. Dans les dix prochaines années, elle devrait être multipliée par mille (x1000) en comparaison avec celle des réseaux sans fil actuels. De ce fait, une évolution technologique est nécessaire pour les futurs systèmes de communication sans fil. L'amélioration de la capacité du réseau passe par l'amélioration de l'efficacité spectrale, l'élargissement du spectre et l'utilisation de plusieurs petites cellules pour augmenter la densité réseau. De plus, une feuille de route pour le développement du système 5G a été proposée par l'organisation Third Generation Partnership Project (3GPP). Elle précise la nécessité d'une meilleure consommation d'énergie, d'une meilleure efficacité spectrale ainsi qu'une capacité de desservir un plus grand nombre d'utilisateurs pour les systèmes de communication sans fil de prochaine génération. Deux techniques pour augmenter l'efficacité spectrale sont à l'étude pour le futur réseau 5G. La première utilise le partage du spectre et des techniques de détection dans le but de rechercher de nouvelles bandes spectrales. La deuxième méthode inclut l'utilisation de technologies avancées de transmission radio qui peuvent potentiellement élever au carré le rapport signal bruit (SNR) ou le rapport signal interférence plus bruit (SINR). Ainsi, l'efficacité spectrale peut s'améliorer grandement en comparaison de celle des systèmes sans fil actuels.

Parmi les technologies avancées de transmission par interface radio, la transmission full-duplex (FD) parait prometteuse dans les milieux académique et industriel étant donné sa capacité d'améliorer l'efficacité spectrale sans avoir besoin d'élargir la bande de fréquence. La technologie FD est ancienne dans le domaine de la communication sans fil et a été utilisée depuis les années 1940 dans les systèmes radar à onde continue. Dans les systèmes FD, un terminal sans fil peut transmettre et recevoir le signal sur la même bande de fréquence pour une tranche temporelle spécifique. Par conséquent, les systèmes FD peuvent potentiellement doubler l'efficacité spectrale comparés aux systèmes half-duplex (HD). La transmission FD peut aussi aider à améliorer le décalage pour les systèmes de relais étant donné qu'un relais peut transmettre simultanément les données au terminal de destination et les recevoir du terminal source. Aussi, étant donné que les données reçues et transmises coexistent en même temps sur le lien de transmission, le signal capturé par un tiers sera un mélange de signaux

qui sont plus difficiles à déchiffrer. De plus, la latence de l'interface radio peut être réduite à l'aide de la réception de signaux de retour tels que les informations sur l'état du canal (CSI) durant la transmission des données. La flexibilité du spectre augmente aussi grâce à la capacité d'émission et de réception sur le même spectre, chaque émetteur-récepteur pouvant utiliser soit une bande de fréquence en transmission FD soit deux bandes de fréquence en transmission HD.

Quoique la technique de transmission FD offre plusieurs avantages, sont défaut majeur, qui l'empêche d'être utilisée dans les réseaux de communication actuels, est le fort effet d'auto-interférence (SI). Comme la distance entre les antennes émettrices et réceptrices pour un terminal est plus courte que la distance entre terminaux, le SI du signal reçu par l'antenne réceptrice d'un terminal provenant de sa propre antenne émettrice est plusieurs fois plus fort que le signal reçu d'un autre terminal.

Récemment, plusieurs études ont porté sur la suppression des effets du SI pour les systèmes FD. Trois techniques principales ont été considérées pour la réduction du SI. La première est la séparation d'antennes qui est une simple technique d'annulation qui augmente la distance entre les antennes émettrices et réceptrices afin de réduire la puissance d'interférence. L'inconvénient de cette méthode est l'augmentation en taille du terminal sans fil. La deuxième technique est l'annulation analogique. Dans cette méthode, un signal additionnel d'annulation est envoyé à l'antenne réceptrice dans le but d'annuler le SI de l'antenne émettrice du même terminal. Finalement, l'annulation numérique peut être utilisée pour réduire le SI en se servant de l'information du signal interférant de l'antenne émettrice, permettant ainsi au récepteur de supprimer le SI de la bande de base.

La combinaison de toutes ces techniques peut supprimer le SI afin que les systèmes FD aient de meilleurs résultats que les systèmes HD. En outre, de nouvelles techniques d'annulation analogiques numériques ont été étudiées et testées. Il a été démontré que le signal d'interférence au récepteur peut être réduit à un niveau comparable au bruit de fond. Grâce aux avancées technologiques considérables dans le domaine du traitement du signal et de conception matérielle, la méthode de la transmission FD a le potentiel de devenir une technologie d'évolution pour les réseaux sans fil de prochaine génération.

Néanmoins, la performance du système FD ne peut être optimale étant donné qu'elle dépend encore de l'allocation des ressources. Plusieurs études ont traité de ce sujet. Cependant, dans ces travaux, on suppose que la technique FD est utilisée uniquement à la station de base, où les utilisateurs utilisent encore le mode HD ou alors en supposant une annulation parfaite du SI, qui est traité comme du bruit, une hypothèse peu réaliste. Par conséquent, le sujet de cette thèse est l'optimisation de ressources pour un cas plus général du réseau FD à accès multiple par division orthogonale de fréquence (OFDMA).

0.2 Objectifs de Recherche et Contributions

L'objectif principal de l'étude réalisée dans cette thèse est le développement de l'algorithme d'allocation de ressources pour les réseaux FD OFDMA dans le but de maximiser le débit total de données. Plusieurs approches différentes au problème d'optimisation sont examinées. De plus, les effets de plusieurs facteurs affectant le débit du système tels que les paramètres d'annulation du SI ou les contraintes de puissance maximale sont aussi considérés. Les contributions de cette thèse sont décrites plus en détails dans ce qui suit.

Les travaux récents sur les systèmes FD de communication sans fil considèrent que la transmission FD est activée uniquement au niveau de la BS pendant que les utilisateurs travaillent en mode HD ou une annulation parfaite du SI est supposée. De ce fait, le chapitre 3 de cette thèse examine un cas plus général des réseaux FD. Le modèle du système étudié dans cette thèse est une seule cellule réseau OFDMA. Tous les terminaux (BS et utilisateurs) sont capables d'utiliser la FD et peuvent basculer entre les modes FD et HD. Notre objectif est de maximiser le débit total du réseau en optimisant conjointement le choix d'attribution de la sous porteuse (SA) et l'allocation de puissance (PA). Étant donné qu'une annulation imparfaite du SI est considérée dans notre travail, le SI est modélisé par un monôme de la puissance de transmission. On commence par formuler le problème d'optimisation comme un programmation entière mixte non-convexe, qui est NP-hard en général. Par la suite, deux approches sont proposées pour résoudre ce problème ainsi que deux algorithmes gloutons et rapides afin de démontrer le gain significatif de notre design. Les contributions principales de cette thèse peuvent être résumées comme suit :

- Un modèle général d'optimisation est proposé afin d'optimiser le débit total de données de notre cellule réseau FD OFDMA. Chaque terminal dans le système est capable d'utiliser une transmission FD. De surcroît, afin d'augmenter encore plus la flexibilité du système, l'utilisateur et la BS peuvent basculer entre les modes FD et HD qu'ils offrent un meilleur débit total de données. L'effet de la puissance de transmission sur le SI est aussi considéré dans notre modèle du système.

- Deux méthodes ont été développées pour résoudre le problème. Dans le premier, le SA est trouvé en utilisant la méthode de correspondance bipartite. La matrice de poids pour cette méthode est créée par une allocation rapide et gloutonne qui trouve le nombre maximal de liens dans une sous porteuse qui offre le meilleur débit de données. Ensuite, à partir du SI donné, on transforme le problème du PA en une fonction concave en utilisant la méthode d'approximation successive convexe.

- Dans la deuxième approche, on développe un algorithme itératif pour résoudre ce problème. Premièrement, les variables SA sont transformées de valeurs entières en valeurs réelles et ensuite à chaque itération elles sont mise à jour par la méthode du gradient. Puis, avec les valeurs du SA mises à jours, le problème du PA est résolu par la méthode d'approximation successive convexe.

- Les résultats des calculs sont présentés pour démontrés l'efficacité de notre algorithme proposé. L'impact des différents paramètres sur les résultats de la méthode d'allocation de ressources sont aussi considérés. Les résultats de simulation montrent aussi la convergence de notre algorithme itératif. De plus, on peut noter que la performance de la méthode proposée est nettement meilleure que l'approche rapide et gloutonne. En outre, le débit total de données du système pour la transmission FD est meilleure que la méthode HD dans la plupart des cas.

Dans la section suivante, notre modèle du système et la formulation du problème sont introduits ainsi que l'algorithme pour le résoudre.

0.3 Modèle du Système et Formulation du Problème

0.3.1 Modèle du Système

On considère une seule cellule réseau FD OFDMA qui se compose d'une BS et N utilisateurs mobiles capables de utiliser une transmission FD. Ainsi, la BS et tous les utilisateurs sont capables de transmettre et recevoir les signaux simultanément sur n'importe quelle sous porteuse (SC). Il y a S SC orthogonales dans la bande de fréquence considérée. $\mathcal{N} = \{1, 2, ..., N\}$ et $\mathcal{S} = \{1, 2, ..., S\}$ sont l'ensemble des utilisateurs et l'ensemble des SC. Dans ce modèle, on suppose aussi que chaque SC peut être attribué au plus à un utilisateur pour la transmission uplink (UL) et au plus à un utilisateur pour la transmission downlink (DL). Le modèle du SA pour le UL et DL est défini par les vecteurs binaires $\vec{X}^{\mathsf{U}} \triangleq \{x^{\mathsf{U}}_{n,s}\}_{n\in\mathcal{N},s\in\mathcal{S}}$ et $\vec{X}^{\mathsf{D}} \triangleq \{x^{\mathsf{D}}_{n,s}\}_{n\in\mathcal{N},s\in\mathcal{S}}$, où chaque composante de $x^{\mathsf{U}}_{n,s}$ et $x^{\mathsf{U}}_{n,s}$ est définie comme suit

$$x_{n,s}^{\mathsf{U}}(\text{or } x_{n,s}^{\mathsf{D}})=\begin{cases}1 \text{ si l'utilisateur } n \text{ utilise SC } s \text{ pour l'UL (ou le DL)},\\ \\ 0 \text{ sinon.}\end{cases} \tag{1}$$

Soit $p_{n,s}^{\mathsf{U}}$ la puissance UL allouée à la SC s par l'utilisateur n et soit $p_{n,s}^{\mathsf{D}}$ la puissance DL allouée à la SC s pour l'utilisateur n par la BS. Le vecteur PA est défini par $\vec{P}$ où $\vec{P} \triangleq \left\{\vec{p}_s^{\mathsf{U}}, \vec{p}_s^{\mathsf{D}}\right\}_{s\in\mathcal{S}}$ et $\vec{p}_s^{\mathsf{D}}$ sont le vecteur de puissance pour la SC s pour UL et DL respectivement. Le CSI parfait pour chaque utilisateur et SC est supposé connu par la BS. On peut commencer à analyser le débit de données réalisé par tous les terminaux dans notre système dans le but de définir notre problème.

Le débit réalisé au niveau de la station de base

Pour une transmission FD, le signal reçu à la BS sur la SC s subit les interférences du signal de transmission DL de la BS sur cette SC. Étant donné que l'annulation d'interférence n'est pas parfaite, il ne sera pas possible de supprimer complètement. Donc, il existe des interférences résiduelles dans la SC. La SI au niveau de la BS provenant de la transmission DL qui correspond à la SC s peut être formulée par :

$$I_s^{\mathsf{U}}\left(\vec{x}_s^{\mathsf{D}}, \vec{p}_s^{\mathsf{D}}\right) = \sum_{n\in\mathcal{N}} x_{n,s}^{\mathsf{D}}\epsilon\left(p_{n,s}^{\mathsf{D}}\right)^{\theta}, \tag{2}$$

où $\vec{x}_s^{\mathsf{D}} = \{x_{n,s}^{\mathsf{D}}\}_{n\in\mathcal{N}}$ est le vecteur SA DL pour la SC s, ϵ et θ sont des facteurs d'échelle fixes qui représentent la qualité de la technique d'annulation de la SI. Quand $\theta = 1$ la puissance de la SI est une fonction linéaire de la puissance transmise. Quand $\theta = 0$ la SI est constante et ne dépend pas de la puissance transmise et peut être traitée comme bruit de fond. Dans ce cas, le débit réalisé au niveau de la BS pour l'utilisateur n sur la transmission UL sur la SC s peut s'écrire:

$$R_{n,s}^{\mathsf{U}}\left(\vec{X}, \vec{P}\right) = \log\left(1 + \frac{x_{n,s}^{\mathsf{U}} G_{n,s}^{\mathsf{U}} p_{n,s}^{\mathsf{U}}}{I_s^{\mathsf{U}}\left(\vec{x}_s^{\mathsf{D}}, \vec{p}_s^{\mathsf{D}}\right) + N_0}\right), \tag{3}$$

où $G_{n,s}^{\mathsf{U}}$ est le gain entre l'utilisateur n et la BS, et N_0 est la puissance du bruit.

Débit réalisé au niveau des utilisateurs

Deux cas peuvent exister quand l'utilisateur n se voit attribuer la SC s pour la transmission DL. Dans le premier cas, l'utilisateur n utilise aussi la même SC s pour la transmission UL. Ainsi, cette transmission UL crée de la SI et peut être calculée comme étant $\epsilon\left(p_{n,s}^{\mathsf{U}}\right)^{\theta}$. Dans le deuxième cas, la SC s est attribuée à l'utilisateur j pour la transmission UL. Ainsi, dans ce cas, la transmission UL de l'utilisateur j crée une interférence sur le signal DL reçu de l'utilisateur n sur la SC s et cette interférence peut être calculée comme suit :

$$I_{j,n,s}^{\mathsf{cr}}\left(\vec{x}_s^{\mathsf{U}},\vec{p}_s^{\mathsf{U}}\right) = x_{j,s}^{\mathsf{U}} G_{j,n,s} p_{j,s}^{\mathsf{U}}, \tag{4}$$

où $G_{n,j,s}$ est le gain d'interférence du canal de l'utilisateur n à l'utilisateur j sur la SC s et $\vec{x}_s^{\mathsf{U}} = \{x_{n,s}^{\mathsf{U}}\}_{n\in\mathcal{N}}$ est le vecteur SA UL pour la SC s. Généralement, l'interférence sur le signal reçu de l'utilisateur n sur la Sc s peut être résumée comme suit :

$$I_{n,s}^{\mathsf{D}}\left(\vec{x}_s^{\mathsf{U}},\vec{p}_s^{\mathsf{U}}\right) = \sum_{j\in\mathcal{N}/n} x_{j,s}^{\mathsf{U}} G_{j,n,s} p_{j,s}^{\mathsf{U}} + x_{n,s}^{\mathsf{U}}\epsilon\left(p_{n,s}^{\mathsf{U}}\right)^{\theta}. \tag{5}$$

Le débit de données réalisé par l'utilisateur n pour la transmission DL sur la SC s peut être s'écrire:

$$R_{n,s}^{\mathsf{D}}\left(\vec{X},\vec{P}\right) = \log\left(1 + \frac{x_{n,s}^{\mathsf{D}} G_{n,s}^{\mathsf{D}} p_{n,s}^{\mathsf{D}}}{I_{n,s}^{\mathsf{D}}\left(\vec{x}_s^{\mathsf{U}},\vec{p}_s^{\mathsf{U}}\right) + N_0}\right). \tag{6}$$

0.3.2 Formulation du Problème

Dans cette section, on formule le problème FD conjointement pour SA et PA en se basant sur l'analyse ci-dessus. Ce problème a pour but de calculer le SA pour les utilisateurs pour les transmissions DL et UL ainsi que la puissance de transmission correspondante à chaque lien afin de maximiser le débit total du réseau. À partir de ces objectifs, notre problème peut être formulé par :

$$\max_{\vec{X},\vec{P}} R_{\mathsf{total}} = \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} R^{\mathsf{U}}_{n,s}\left(\vec{X},\vec{P}\right) + R^{\mathsf{D}}_{n,s}\left(\vec{X},\vec{P}\right) \tag{7a}$$

$$\text{s.t.} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} p^{\mathsf{D}}_{n,s} \leq P_{\mathsf{BS}}, \tag{7b}$$

$$\sum_{s\in\mathcal{S}} p^{\mathsf{U}}_{n,s} \leq P_n,\ \forall n \in \mathcal{N}, \tag{7c}$$

$$\sum_{n\in\mathcal{N}} x^{\mathsf{U}}_{n,s} \leq 1 \text{ and } \sum_{n\in\mathcal{N}} x^{\mathsf{D}}_{n,s} \leq 1,\ \forall s \in \mathcal{S}, \tag{7d}$$

$$x^{\mathsf{U}}_{n,s}, x^{\mathsf{D}}_{n,s} \in \{0,1\},\ \forall n \in \mathcal{N},\ \forall s \in \mathcal{S}. \tag{7e}$$

Dans ce problème d'optimisation, P_{BS} et P_n définissent respectivement la valeur maximum de la puissance de transmission de la station de base et et l'utilisateur n peuvent utiliser. Les deux premières contraintes (7b) et (7c) sont la valeur maximum de la puissance pour la BS et chaque utilisateur. Les contraintes (7d) imposent l'attribution de la SC s au plus à un utilisateur pour les transmissions DL et UL. On peut facilement voir que le problème d'optimisation (7) est un programme entier mixte, qui est NP-hard en général et nécessite une complexité exponentielle pour être résolu. Inspiré par un travail récent sur PA et SA, on propose un algorithme itératif dans la section qui suit afin de trouver la solution optimal locale pour le problème (7). Dans la section suivante, nous proposons deux algorithmes. Le premier est un algorithme de couplage dans un graphe biparti avec les poids calculés en utilisant une approche rapide et gloutonne. La deuxième résout le problème entier mixe en utilisant la méthode du gradient en transformant les variables entières en variables réelles.

0.4 Algorithme

Dans cette section, nous présentons deux méthodes pour résoudre le problème SA : la méthode de couplage dans un graphe biparti et la méthode du gradient. Le problème PA peut être résolu par la méthode de l'approximation successive convexe.

0.4.1 Méthode de Couplage Dans un Graphe Biparti

La méthode de couplage dans un graphe biparti est utillisée pour résoudre le problème SA en supposant la solution PA a été déterminée. Étant donné que chaque SC peut avoir au plus une transmission DL et une transmission UL pour N utilisateurs, il y aura N^2 paires possibles d'utilisateurs dans le mode FD. Étant donné que la SC peut être aussi utilisée dans le mode HD, on aura $2N$ autres cas à considérer. Ainsi, on définit une matrice M $K \times K$ où $K = N^2 + 2N$. Les lignes $\{1, 2, .., N^2\}$ dans la matrice M représentent la paire d'utilisateurs UL et DL en mode FD et les lignes $\{N^2 + 1, ..., N^2 + 2N\}$ sont en mode HD. Les colonnes $\{1, ..., S\}$ représentent les SC et le reste des colonnes sont vides afin que la matrice puissent être élevée au carré. La valeur de chaque élément de la matrice est le débit obtenu quand la paire d'utilisateurs (n, j) se voit attribuer la SC s.

Les nouvelles variables de puissance q_s^{U} et q_s^{D} sont introduites pour représenter la puissance de transmission pour tous les utilisateurs sur chaque SC pour les transmissions UL et DL. La relation entre q_s^{U} et $p_{n,s}^{\mathsf{U}}$, q_s^{D} et $p_{n,s}^{\mathsf{D}}$ peut être donnée par

$$q_s^{\mathsf{U}} = \sum_{n \in \mathcal{N}} x_{n,s}^{\mathsf{U}} p_{n,s}^{\mathsf{U}}, \quad q_s^{\mathsf{D}} = \sum_{n \in \mathcal{N}} x_{n,s}^{\mathsf{D}} p_{n,s}^{\mathsf{D}}. \tag{8}$$

Ainsi, la valeur de l'élément pour la ligne a et la colonne s avec $a \in \{1, ..., N^2\}$ et $s \in \mathcal{S}$ peut être calculée comme suit

$$W_{a,s}\left(q_s^{\mathsf{D}}, q_s^{\mathsf{U}}\right) = \log\left(1 + \frac{q_s^{\mathsf{U}} G_{j,s}^{\mathsf{U}}}{\epsilon\left(q_s^{\mathsf{D}}\right)^{\theta} + N_0}\right) + \log\left(1 + \frac{G_{n,s}^{\mathsf{D}} q_s^{\mathsf{D}}}{G_{j,n,s} q_s^{\mathsf{U}} + \epsilon_s^{\mathsf{U}}\left(q_s^{\mathsf{U}}\right)^{\theta} + N_0}\right), \tag{9}$$

où $n = \lceil a/N \rceil$ et $j = a - \lfloor a/N \rfloor N$.

Pour les lignes $\{N^2 + 1, ..., N^2 + N\}$ correspondant à la transmission DL en mode HD, les valeurs de l'élément dans la colonne $\{1, ..., S\}$ sont

$$W_{a,s}\left(q_s^{\mathsf{D}}\right) = \log\left(1 + \frac{G_{n,s}^{\mathsf{D}} q_s^{\mathsf{D}}}{N_0}\right), \tag{10}$$

où $n = a - N^2$.

Les lignes $\{N^2 + N + 1, ..., N^2 + 2N\}$ présentent le cas d'une transmission UL en mode HD. Les valeurs de l'élément dans les colonnes $\{1, ..., S\}$ sont

$$W_{a,s}\left(q_s^{\mathsf{U}}\right) = \log\left(1 + \frac{G_{n,s}^{\mathsf{U}} q_s^{\mathsf{U}}}{N_0}\right), \tag{11}$$

où $n = a - N^2$. Le reste de la matrice M sera rempli de 0.

Étant donné que M est une matrice carrée où les valeurs de chaque élément sont considérées comme poids pour une SC s et qu'on veut trouver la combinaison qui offre le débit maximal, le problème est un problème d'affectation. Soit $\tilde{x}_{a,s} \in \vec{\tilde{X}}$ la variable d'attribution binaire pour notre matrice de poids M alors notre problème SA basé sur la couplage dans un graphe biparti peut être formulé comme suit

$$\max_{\vec{\tilde{X}}} \sum_{a\in\mathcal{K}} \sum_{s\in\mathcal{S}} W_{a,s}\tilde{x}_{a,s} \tag{12}$$

$$\sum_{a\in\mathcal{K}} \tilde{x}_{a,s} = 1,\ \forall s \in \mathcal{S}, \tag{13}$$

$$\tilde{x}_{a,s} \in \{0,1\},\ \forall a \in \mathcal{K},\ \forall s \in \mathcal{S}. \tag{14}$$

On peut utiliser l'algorithme Kuhn-Munkres pour trouver la solution optimale du problème (12) en temps polynomial.

0.4.2 La Méthode du Gradient

Cette section examine la méthode du gradient afin de trouver un bon SA pour tous les utilisateurs avec une PA donnée sur toutes les SC pour les transmissions UL et DL en mettant à jour les variables SA en utilisant la méthode gradient. Supposons que $\vec{Q}$ soit donné, on remplace le terme quadratique $x^{\mathsf{D}}_{n,s}x^{\mathsf{U}}_{j,s}$ dans $\epsilon^{\mathsf{U}}_s(\vec{X})$ par les variables binaires suivantes

$$y_{n,j,s} = x^{\mathsf{D}}_{n,s}x^{\mathsf{U}}_{j,s},\quad \forall n, j \in \mathcal{N}. \tag{15}$$

On peut noter que $y_{n,j,s} = 1$ si SC s est attribuée à l'utilisateur n pour la transmission DL et l'utilisateur j en transmission UL et $y = 0$ sinon. Quand $y_{n,j,s} = 1$ le débit atteint sur la SC s pour un $\vec{Q}$ donné peut être calculée comme suit

$$\begin{aligned} R_{n,j,s} =& \log\left(1 + \frac{G^{\mathsf{U}}_{j,s}q^{\mathsf{U}}_s}{\epsilon\left(q^{\mathsf{D}}_s\right)^{\theta} + N_0}\right) \\ &+ \log\left(1 + \frac{G^{\mathsf{D}}_{n,s}q^{\mathsf{D}}_s}{I'^{\mathsf{D}}_{\vec{Q},s}(n,j) + N_0}\right), \end{aligned} \tag{16}$$

où

$$I'^{\mathsf{D}}_{\vec{Q},s}(n,j) = \begin{cases} \epsilon\left(q_s^{\mathsf{U}}\right)^{\theta} & \text{if } n = j, \\ G_{j,n,s}q_s^{\mathsf{U}} & \text{if } n \neq j. \end{cases} \tag{17}$$

Étant donné les valeurs of q_s^U et q_s^D, on optimise l'allocation $y_{n,j,s}$:

$$\max_{\vec{Y}} \; R_{\vec{Q}}(\vec{Y}) = \sum_{\forall(n,j)} \sum_{s\in\mathcal{S}} R_{n,j,s}y_{n,j,s} \tag{18a}$$

$$\text{s.t.} \; \sum_{n\in\mathcal{N}} \sum_{s\in\mathcal{S}} q_s^{\mathsf{U}} y_{n,j,s} \leq P_j, \;\; \forall j \in \mathcal{N}, \tag{18b}$$

$$\sum_{\forall(n,j)} y_{n,j,s} \leq 1, \;\; s \in \mathcal{S}, \tag{18c}$$

$$y_{n,j,s} \in \{0,1\}, \; \forall(n,j), \; \forall s \in \mathcal{S}, \tag{18d}$$

où $\vec{Y}$ représente le vecteur généré par toutes les variables $y_{n,j,s}$. Même si le problème (18) est un programme entier non-convexe, son optimum global peut être trouvé. En transformant la dernière contrainte (18d) en $0 \leq y_{n,j,s} \leq 1$, le problème (18) devient un programme linéaire en $y_{n,j,s}$, dont les solutions optimales peuvent être trouvées efficacement par les techniques d'optimisation convexes standards. La solution optimale obtenue de ce programme linéaire se trouve dans un sommet où $y_{n,j,s}$ sera égale soit à 0 ou à 1. Ainsi, étant donné $\vec{Q}$ et $R_{n,j,s}$, la résolution du programme linéaire donnera le SA optimal pour chaque utilisateur. Cependant, une fois que $y_{n,j,s}$ prend la valeur de 0 ou 1, la valeur de l'affectation pour chaque utilisateur peut s'avérer être un point à partir duquel il n'est plus possible d'optimiser la puissance. Afin de surmonter ce problème critique, on modifie graduellement les variable $y_{n,j,s}$ en se déplaçant dans la direction du gradient. On peut alors optimiser les puissances avec plus de précision. En particulier, le gradient de $y_{n,j,s}$ comme dans la fonction objectif du problème (18) peut être donné par $R_{n,j,s}$. Ainsi, la méthode de projection du gradient peut être décrite comme suit

$$Y^{\vec{k+1}} = P_{\Omega}(\vec{Y^k} + \lambda^k \vec{R}), \tag{19}$$

où $\vec{R}$ représente le vecteur généré par $R_{n,j,s}$, λ_k est la taille du pas du gradient qui diminue lentement, et $P_\Omega(\cdot)$ définit la projection qui est décrite par le problème quadratique suivant

$$\min_{\vec{Y}} \; ||y_{n,j,s} - \hat{y}_{n,j,s}||^2 \tag{20a}$$

$$\text{sous les} \quad \text{constraintes (18b) et (18c),}$$

$$0 \leq y_{n,j,s} \leq 1, \; \forall (n,j), \; \forall s \in \mathcal{S}, \tag{20b}$$

où $\hat{y}_{n,j,s} = y^k_{n,j,s} + \lambda^k R_{n,j,s}$. Le processus de mise à jour ci-dessus peut garantir une convergence à la valeur locale optimale de $y_{n,j,s}$ si λ_k est choisie de façon que $\lambda_k \to 0$ quand $k \to \infty$.

0.4.3 Algorithme d'allocation de ressources

Dans cette section, on présentera l'algorithme qui sera utilisé dans la simulation.

0.4.4 Algorithme Proposé Basé sur le Couplage FD

Le problème SA est résolu en utilisant la méthode de couplage et le problème PA est résolu par l'algorithme d'approximation successive convexe. Dans le but de calculer les poids de la matrice de couplage, une allocation rapide et gloutonne sera employée afin de trouver une solution SA initiale et ensuite la solution PA initiale pour le calcul des poids peut être trouvée en appliquant la méthode d'approximation successive convexe.

Algorithme Basé sur le Couplage FD

1: Utiliser une attribution gloutonne avec une allocation uniforme de puissance afin d'avoir la valeur initiale de $\vec{X}$.
2: À la valeur initiale de $\vec{X}$, appliquer l'approximation successive convexe afin d'avoir $\vec{P}$.
3: Utiliser $\vec{P}$, (9), (10), et (11) afin de calculer les poids dans la matrice de couplage M.
4: Résoudre M pour $\vec{X}$.
5: Appliquer l'approximation successive convexe afin d'avoir $\vec{P}$.
6: Calculer le débit total de données en (7) se servant de $\vec{P}$ et $\vec{X}$.

0.4.5 Algorithme du gradient FD Proposé

Dans notre algorithme du gradient FD, les variables SA sont d'abord transformées de valeurs entières en valeurs réelles et ensuite, dans chaque itération, elles sont lentement mises à jour par une méthode de gradient. Ensuite, avec les variables SA mises à jour, le problème PA est résolu par la méthode d'approximation successive convexe. Les détails de l'algorithme proposé sont décrits ci-dessous

ALGORITHME DE GRADIENT FD

1: Commencer: $q_s^{\mathsf{D}} = P_{\mathsf{BS}}/S$, $q_s^{\mathsf{U}} = \min_{n\in\mathcal{N}} P_n/S \ \forall s \in \mathcal{S}$.
2: **repeat**
3: Fixer $\vec{Q}$ puis mettre à jour $\vec{X}$ en utilisant (19).
4: Fixer $\vec{X}$, résoudre $\vec{Q}$ par la méthode d'approximation successive convexe.
5: **until** La convergence.
6: Retourner $\vec{X}$ de $\vec{Y}$ comme suit $x_{n,s}^{\mathsf{D}} = \sum_{j\in\mathcal{N}} y_{n,j,s}$, $x_{j,s}^{\mathsf{U}} = \sum_{n\in\mathcal{N}} y_{n,j,s}$.

0.4.6 Algorithme FD Gloutonne

Cet algorithme est utilisé pour calculer la valeur initiale des poids pour l'algorithme FD.

0.4.7 Algorithme HD Gloutonne

Dans cet algorithme chaque SC se voit attribuer au plus un lien, soit une transmission UL ou DL. L'allocation uniforme de puissance est appliquée pour cette méthode aussi. Pour SA, chaque SC est attribuée à l'utilisateur avec la transmission UL ou DL avec le plus haut débit réalisable au lieu d'une paire de transmission UL et DL comme dans les algorithmes FD.

0.5 Résultats de Simulation

On considère une seule cellule réseau dans laquelle les utilisateurs sont placés arbitrairement. Les gains de canal sont générés en considérant un évanouissement Rayleigh et une perte de trajet qui est modelée en se basant sur le modèle WINNER-II par $PL(d) = A\log_{10}(d) + B + C\log_{10}(f_c/5)$, où d est la distance entre deux terminaux. Les détails des paramètres utilisés dans notre simulation sont montrés dans le tableau 3.1 suivant. Dans la figure 3, la puissance maximale de la BS et des utilisateurs sont multipliés par un facteur d'échelle Ω afin d'analyser l'effet de la puissance sur le débit total de données du système.

Table 1: Paramètres de la Simulation

Paramètres	Valeurs
Paramètres du modèle WINNER-II	A = 36.8, B = 43.8, C = 23, and $f_c = 2.5GHz$
Distance minimale	50m
Distance maximale	100m
Nombre d'utilisateurs	10
Nombre de porteuse	20
Puissance de la station de base	4W
Puissance de l'utilisateur	0.4W
Puissance du bruit N_0	10^-12W
ϵ	10^-12
θ	0.5

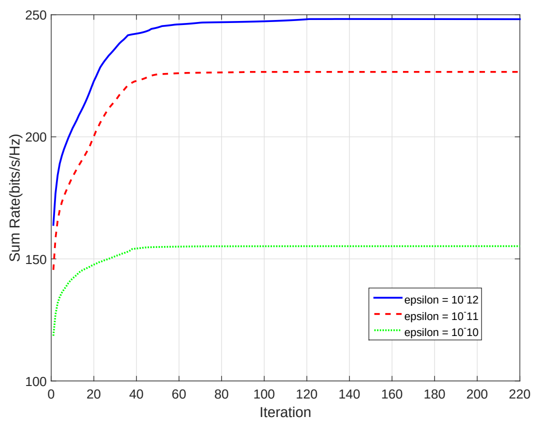

Figure 1: Le débit total vs l'index d'itération

D'abord, on examine la convergence de notre algorithme du gradient en montrant les variations du débit total du système qui correspondent à différentes valeurs de ϵ pour un nombre d'itération dans la figure 1. On fixe $\theta = 1$. On peut observer que notre algorithme converge pour les deux boucles interne et externe. Quand la valeur de θ diminue, le nombre d'itération nécessaire pour la convergence augmente. Ceci est dû au fait qu'il existe plus de SI avec une grande valeur de θ, ainsi le nombre de choix pour l'allocation est plus petit.

Dans les figures 2 et 3, on montre les variations du débit total réalisés par notre algorithme basé sur le couplage FD et Algorithme de gradient FD ainsi que deux algorithmes gloutonnes présentés dans les sections précédentes par rapport aux changements de quelques paramètres du réseau tels que le facteur d'interférence ϵ dans la figure 2 et la puissance de transmission maximale dans la figure 3. Comme on peut voir dans ces figures, l'algorithme basé sur le couplage FD et l'algorithme de gradient FD surpassent les deux algorithmes avides dans tous les scénarios étudiés. On peut aussi noter que l'algorithme de gradient réalise de meilleurs résultats que l'algorithme de couplage. Cependant, il faut 100 itérations pour atteindre la solution finale quand l'algorithme de couplage n'en fait qu'une. De plus, on peut voir tous les algorithmes FD réalisent de meilleurs débits totaux de données que l'algorithme HD.

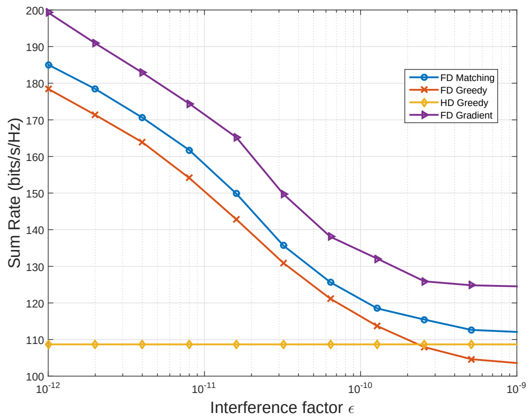

Figure 2: Le débit total vs le facteur d'interférence ϵ.

Comme on peut le voir dans la figure 2, une valeur plus grande du facteur d'interférence ϵ résulte en un débit total moindre pour notre système quand il est dans un mode FD. Cela peut être expliqué facilement étant donné que les grandes valeurs de ϵ se traduisent par le fait que l'annulation de la SI est moins efficace dans la prévention des interférences et réduit les avantages des techniques FD. De plus, on peut observer que quand ϵ est plus grand que 10^{-10}, la performance de l'algorithme FD gloutonne devient pire que celle du HD et le débit total des deux algorithmes proposés est encore meilleure que celle du HD.

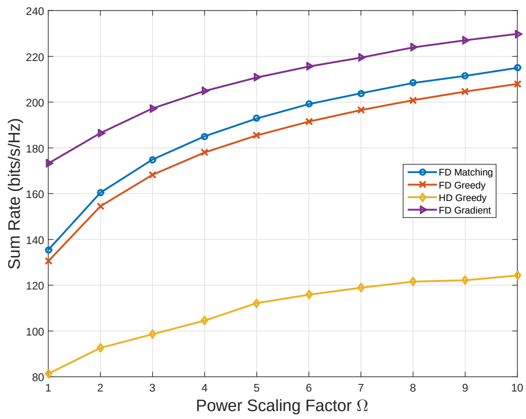

Figure 3: Le débit total vs le facteur d'échelle Ω.

Dans la figure 3, augmenter la puissance de transmission de la BS et des utilisateurs à travers l'augmentation du facteur d'échelle Ω résulte en un plus grand débit total du réseau comme espéré. On peut remarquer que pour les basses valeurs de puissance, l'écart entre l'algorithme de gradient et le reste est grand. Quand la puissance augmente, l'écart s'amincit étant donné que l'effet de l'augmentation de puissance commence à saturer. De plus, on peut voir dans la figure 2 que le débit total de l'algorithme basé sur le couplage FD est environ 5% plus élevé que celui de l'algorithme FD gloutonne et presque deux fois meilleur que celui de l'algorithme HD gloutonne. En général, l'algorithme du gradient réalise les meilleurs résultats en comparaison avec le reste. La performance de la méthode de couplage n'est également pas meilleure à cause des poids de la matrice de couplage qui ne peuvent pas refléter tous les cas possibles qui peuvent exister dans notre modèle.

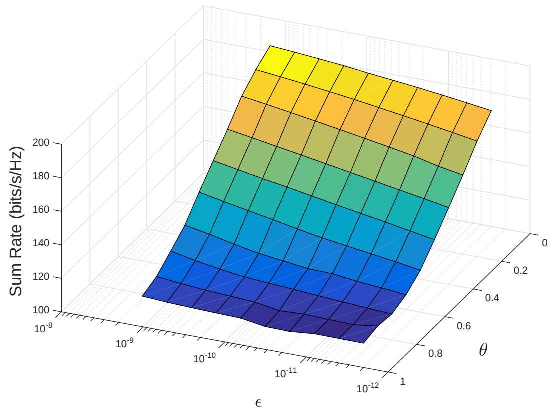

Figure 4: Le débit total vs theta vs epsilon.

La figure 4 montre l'influence des paramètres d'annulation de la SI ϵ et θ sur le débit total de notre algorithme proposé. On peut voir qu'une plus petite valeur de θ résulte en un plus bas débit total. Ceci est dû au fait que la valeur de la puissance est plus petite que 1, ainsi avec une valeur de $0 \leq \theta \leq 1$, p^θ devient plus grande que la valeur originale de p. De plus, le changement de θ résulte en un changement plus rapide dans le débit total du système que le changement de ϵ. Ceci s'explique par le fait que θ soit une puissance alors que ϵ ne peut avoir qu'un effet linéaire sur le signal d'interférence.

Abstract

Full-duplex (FD) has recently been considered as a technological evolution for next-generation wireless networks with the expectation of significant capacity increase. In FD systems, a wireless terminal can transmit and receive a signal on the same frequency band at a particular time slot. Therefore, FD systems can potentially double the spectral efficiency relatively to the Half-duplex (HD) ones. The advantages of FD have come from the combination of various techniques, including antenna design, analog and digital cancellation, to effectively reduces self-interference caused by the transmitted signal of a terminal to itself. Nevertheless, the performance of the FD sytem cannot be as good since it still depends on the resource allocation design.

This thesis focuses on the resource allocation problem in a full-duplex (FD) multiuser single cell system consisting of one FD base-station (BS) and multiple FD mobile nodes. In particular, we are interested in jointly optimizing power allocation (PA) and subcarrier assignment (SA) for uplink (UL) and downlink (DL) transmission of all users to maximize the system's sum-rate. First, the joint optimization problem is formulated as a nonconvex mixed integer program, a notoriously difficult nonconvex problem. Then two approaches are proposed to solve this problem. In the first method, the SA problem is solved by the bipartite matching method and then the PA is solved by employing the successive convex approximation for low complexity(SCALE) algorithm. In the second method, an iterative algorithm is developed to solve this problem efficiently. In each iteration, the SA is relaxed into real numbers and updated by a gradient method, whereas the PA is again solved by the SCALE algorithm. Two greedy algorithms are further introduced in order to measure the effectiveness our design. Finally, numerical results are presented to demonstrate the significant gains of the proposed algorithms in comparison with the conventional approaches.

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Glossary

Abbreviations

$3GPP$	Third generation partnership project
BS	Base station
CSI	Channel state information
DL	Downlink
FD	Full-duplex
HAP	Hybrid access-point
HD	Half-duplex
$OFDM$	Orthogonal frequency division multiplexing
$OFDMA$	Orthogonal frequency division multiple access
PA	Power allocation
QoS	Quality of service
SA	Subcarrier assignment
SC	Subcarrier
$SCALE$	Successive convex approximation for low complexity
SI	Self-interference
$SINR$	Signal-to-interference-plus-noise

SNR	Signal-to-noise ratio
UL	Uplink
$WPCN$	Wireless-powered communication network

Notations

$\bar{z}_s^{\mathsf{D}}$,α_s^{D},β_s^{D}	Successive convex approximation for low complexity parameters of subcarrier s for downlink transmission
$\bar{z}_s^{\mathsf{U}}$,α_s^{U},β_s^{U}	Successive convex approximation for low complexity parameters of subcarrier s for uplink transmission
$\bar{z}_{n,s}^{\mathsf{D}}$,$\alpha_{n,s}^{\mathsf{D}}$,$\beta_{n,s}^{\mathsf{D}}$	Successive convex approximation for low complexity parameters of user n on subcarrier s for downlink transmission
$\bar{z}_{n,s}^{\mathsf{U}}$,$\alpha_{n,s}^{\mathsf{U}}$,$\beta_{n,s}^{\mathsf{U}}$	Successive convex approximation for low complexity parameters of user n on subcarrier s for uplink transmission
ϵ,θ	Interference scaling factor
Ω	Power scaling factor
$\tilde{x}_{a,s}$	Binary assignment variable for weight matrix M
d	Distance between two terminals
$G_{n,s}^{\mathsf{D}}$	Downlink channel gain between node n and the base station
$G_{n,s}^{\mathsf{U}}$	Uplink channel gain between node n and the base station
$G_{n,j,s}$	Interference channel gain from user n to user j over subcarrier s
$I_{j,n,s}^{\prime\mathsf{D}}$,$I_{j,n,s}^{\prime\prime\mathsf{D}}$	Interference at user n from user j on subcarrier s
$I_{j,s}^{\prime\mathsf{U}}$,$I_{j,s}^{\prime\prime\mathsf{U}}$	Interference at base station from user j on subcarrier s
$I_{j,n,s}^{\mathsf{cr}}$	Cross-interference power from user j to user n over subcarrier s
$I_{n,s}^{\mathsf{D}}$	Interference on the received signal of user n over subcarrier s
I_s^{U}	Self-interference at the base station from DL transmission on subcarrier s

j	Uplink node index
M	Weight matrix
N	Number of nodes
n	Node index
N_0	Receiver noise power
P_{BS}	Power budget of base station
$p_{n,s}^{\mathsf{D}}$	Downlink power allocation on subcarrier s of node n
$p_{n,s}^{\mathsf{U}}$	Uplink power allocation on subcarrier s of node n
P_N	Power budget of node
q_s^{D}	Power allocated to subcarrier s for downlink transmission
q_s^{U}	Power allocated to subcarrier s for uplink transmission
$R_s'^{\mathsf{D}}$	Rate achieved at the base station on downlink transmission over subcarrier s
$R_s'^{\mathsf{U}}$	Rate achieved at the base station on uplink transmission over subcarrier s
$R_{n,s}^{\mathsf{D}}$	Rate achieved by the user n on the downlink transmission over subcarrier s
$R_{n,s}^{\mathsf{U}}$	Rate achieved at the base station for the user u on the uplink transmission over subcarrier s
$R_{n,j,s}$	Rate of subcarrier s with user n on downlink and user j on uplink transmission
S	Number of subcarrier
s	Subcarrier index
$W_{a,s}$	Value of the cell on row a^{th}, column s^{th}
$x_{n,s}^{\mathsf{D}}$	Allocation variable for downlink transmission

$x^{\mathsf{U}}_{n,s}$	Allocation variable for uplink transmission
$y_{n,j,s}$	Assignment variable for subcarrier s with user n on downlink and user j on uplink transmission

Chapter 1

Introduction

1.1 Motivation

In next-generation wireless communication systems, boosting the system capacity is one of the most important factors because of the continous growth in demand for data traffic: within the next ten years, it is expected to increase thousand-fold (1000x) in comparison with the demand of the current 4G wireless networks. Thus, a technological evolution is a key requirement for the future wireless communication system [1]. The goal to enhance network capacity can be achieved through improving spectral efficiency, extending the spectrum range and utilizing many small cells for network densification [2]. Additionally, a roadmap for the development of 5G system has been proposed by the Third Generation Partnership Project (3GPP). This roadmap encompasses the need for better energy consumption and spectral efficiency along with the capability to support greater numbers of users for the next generation wireless communication system [3]. There are two potential techniques for increasing spectral efficiency that have been considered for 5G. The first method utilizes spectrum sharing and sensing techniques in order to look for new spectrum [4]. The second method involves the use of advanced air interface transmission technologies which can potentially square the signal-to-noise ratio (SNR) or signal-to-interference-plus-noise ratio (SINR). Thus, the spectral efficiency can become much greater than the current wireless systems [3].

Among the advanced air interface transmission technologies, full-duplex(FD) transmission has been considered as a promising method in both academia and industry since it is capable of improving spectral efficiency without the need to expand the frequency band. FD technology has a long history in the wireless communication field and has been used since as far as the 1940s in continous wave radar system [5]. In FD systems, a wireless terminal can transmit and receive signal at the same time and on the same frequency. Therefore, FD systems can potentially double the spectral efficiency relatively to the half-duplex (HD) ones [6, 7]. FD transmission can also help to improve end-to-end delay in relay system since a relay terminal can simultaneously transmit data to the destination node and receive data from the source node [8] Moreover, because data is simultaneously sent and received on the same link, eavesdroppers can only capture mixed signals that are more difficult to decipher [9]. Additionally, the air interface latency can be reduced with the reception of feedback signalling signals such as channel state information(CSI) during data transmission [7]. The flexibility of spectrum is also increased thanks to the capability to receive and transmit on the same spectrum, each transceiver can have the option to use one frequency band in FD transmission or two frequency bands in HD transmission [10].

Even though the FD transmission technique has many advantages to offer, its main drawback which prevents this technique from being used in current wireless communication networks is the severe effect of the self-interference (SI) as shown in Fig.1.1. Since the distance between the reception and transmission antennas at a node is much shorter than the distance between nodes, the SI from the transmitted signal to the receive antenna at the node is many times stronger than the received signal [11].

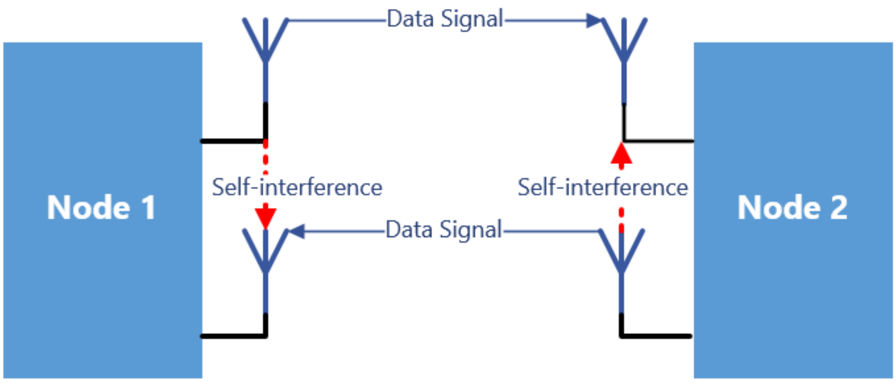

Figure 1.1: Full-duplex wireless communications.

In recent times, there have been many studies focusing on supressing the effects of SI in FD systems.Three main techniques have been considered for reducing the SI. The first one is antenna separation which is a simple cancellation technique that increases the distance between antennas to reduce the interference power. The downside of this method is the increase in size of the wireless nodes. The second technique is the analog cancellation. In this method, an additional cancelling signal is sent to the receiving antenna in order to cancel out the SI from the transmission antenna of the same node. Finally, the digital cancellation can also be used for reducing the SI by using the information of the interfering signal from the transmit antenna, so the receiver can remove it from the baseband. Fig. 1.2 shows a model of the SI cancellation techniques.

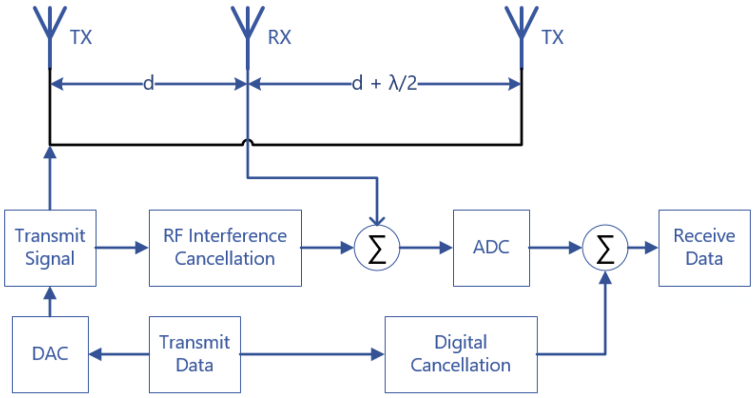

Figure 1.2: Example of SI cancellation at each node.

By combining all of these techniques, the SI can be suppressed to a certain degree such that FD systems can attain better performance than HD system [12, 13]. Additionally, new analog and digital cancellation techniques were studied and experimented. It is shown that the interference signal at the receiver can be successfully reduced to the noise floor [14]. Thanks to the considerable growth in signal processing and hardware design technology, FD transmission has the potential to become a technological evolution for next-generation wireless network.

Nevertheless, FD performance cannot be as good since it still depends on resource allocation design [15]. There have been many studies focusing on this topic. In [16], a power control protocol has been studied to maximize the minimum signal-to-interference-plus-noise (SINR) of all UL and DL links. In [17], Ju et al. jointly optimize the time and power allocations in the wireless-power communication network to maximize the user's weighted sum-rate. However, in these works, it is assumed that only the base station operates in FD, whereas the users still work in HD mode. Additionally, SA is not considered. Recently, [18] studies have been made on jointly optimizing PA and SA design for the wireless network consisting FD base station and FD users. However, perfect SI cancellation is considered in this work where SI is treated as noise, which is not practical. Therefore, the subject of this thesis is the resource optimization for a more general case of FD orthogonal frequency division multiple access (OFDMA) network. In the following, we present a literature survey for the resource allocation topic in FD systems and discuss the research objectives of this thesis.

1.2 Literature Review

In this section, we will review current work on the topic of resource allocation for orthogonal frequency division multiplexing (OFDM) and orthogonal frequency division multiple access (OFDMA) networks for both HD and FD transmission.

1.2.1 Resource Allocation in HD Transmission

In single cell scenario in HD transmission, it was shown that the optimal sum-rate maximization on the uplink side can be achieved by separating subcarrier allocation from power allocation [19, 20]. Each subcarrier is assigned to the user with the best CSI corresponding to that subcarrier, next the water-filling algorithm is applied to allocate the power. Additionally, in order to ensure the fairness of the system, the utility function can also represent system fairness instead of just the sum-rate [19, 20]. Besides the sum-rate maximization, another approach to the optimization of single cell OFDM network is the minimization of transmit power while the quality of service (QoS) is still met. This object is achieved through bit loading over the assigned subcarriers [21]. As studied in [22, 23], the optimal solution for the sum-rate maximization in OFDMA system is obtained by computing the Lagrange multipliers of the power constraints of each assigned user. In the downlink transmission, since the base station (BS) controls all the power, only one power constraint is needed [22]. In the uplink transmission, the power allocated to the subcarrier is controlled by the users, so it will require one Lagrange multiplier for each user and these parameters can be computed by the subgradient method [23].

Besides the instantaneous scheduling, resource allocation is another technique that can be used to optimize OFDMA systems. In [22, 24, 25, 26], the optimization of ergodic weighted sum-rate for OFDMA systems with exclusive subcarrier allocation and maximum power constraints is studied. Additionally, [25, 26] also include the minimum rate constraints, which will guarantee the fairness among the users. In [26], the authors examine an ad-hoc cognitive radio network in which the primary users are subjected to rate constraints and the goal is to maximize the ergodic weighted sum-rate. The ergodic weighted sum-rate maximization for downlink transmission of the OFDMA system is considered in [22].

On the other hand, [24, 25] also study the maximization of ergodic weighted sum-rate for the OFDMA network but in uplink transmission in which only the BS knows the CSI. In [22, 24, 25, 26], the optimization problem of the weighted sum-rate is converted into a convex utility maximization problem, then the dual problem which is proved to have zero dual gap is solved. In order for the solution to meet the transmit power constraint along with the rate constraint in [25, 26], the Lagrangian variables are calculated using the subgradient method.

In single cell OFDMA network, there is no interference since the intracell interference can be neglected thanks to the orthogonality of the subcarriers and the exclusivity of subcarrier allocations within the cell. However, in the case of multicell OFDMA network, the intercell interference is an important factor to be considered in the optimization problem. In [27], the problem of cochannel interference mitigation is solved by base station coordination in the downlink of the OFDMA wireless network. By assuming that coordinated access points only transmit CSI, the set of cochannel users and the power allocation across tones are selected in order to maximize the system sum-rate with the constraints of maximum power budget per BS. In [28], the mitigation of the interference is done by downlink scheduling where each BS will randomly turn off certain subcarriers. On the other hand, the power allocation for downlink transmission in a multicell wireless network to maximize the sum-capacity under power constraints for each BS is studied in [29]. In this paper, it can be seen that for two cells, the optimal power control is binary. When there are more the two cells, the binary power control still results in a negligible loss in capacity. In [30], a distributed algorithm for allocating power along with scheduling was proposed. [31] studies resource allocation for downlink transmission of a multicell OFDMA network without cooperation between BS. In order to minimize interference, a price proportional to the transmit power is used. In [32], the author studies the uplink transmission of the multicell OFDMA system in which scheduling is also considered. The network employs distributed scheduling scheme where each user carries out power control based on the price imposed by the network. The price is enforced on the total power that is transmitted by that user instead of the power allocated to the subcarrier. Perfect knowledge of CSI, transmit power and subcarrier assignment of other users is available to every user in the system. Each user will perform their own complex power control operation based on the price information iteratively.

1.2.2 Resource Allocation in FD Transmission

Unlike the HD communication network which has no intracell interference, the FD communication network must deal with the SI caused by transmitting and receiving signals on the same spectrum. Therefore, the performance of a FD system is greatly affected by the resource allocation design [15]. Thus, many studies focusing on this topic have been done. In [33], the sum-rate of wireless FD bidirectional transmissions is maximized by optimal power allocation among FD source nodes. [34] considers a FD decode-and-forward relay channel in which the optimum power allocation schemes are subject to individual power constraints. Nevertheless, because of the SI from the transmission power of each node with the FD systems, the resource optimization problem for FD wireless communication network is non-convex which is difficult to solve optimally. Thus, recent studies on FD systems normally consider FD only at one terminal of the transmission line in order to simplify the problem [17, 35] or assume perfect SI cancellation [18]. In [17], the wireless-powered communication network (WPCN) is considered. The aim of the paper is to optimize resource allocation in the system in which one hybrid access-point (HAP) working in FD transmission mode sends wireless energy to the users working in HD mode. The case of perfect SI cancellation and imperfect SI cancellation are both considered.

In [35], the resource pairing problem for the OFDMA system is solved by using the matching technique. In this paper, the author considered a FD OFDMA cellular network in which the BS must assign the subcarriers to the pairs of users in order to create a FD transceiver unit. For each pair of user, one user is the transmitter and the other acts as a receiver. In other words, only the BS is capable of performing FD transmission, all the mobile nodes can only work in HD mode. The subcarrier can only be assigned to at most one pair of users. The matching algorithm will run iteratively until it reaches the equilibrium point of the matching. The power allocation problem is not considered in this study.

In [18], the paper examines a single cell FD OFDMA network. The system contains one BS and multiple mobile nodes. Both the BS and mobile nodes are capable of FD transmission. The goal of this paper is the maximization of system sum-rate by jointly optimizing subcarrier assignment and power allocation. An iterative algorithm is proposed to solve this optimizing problem. Each subcarrier in the system is assigned through a greedy method, then the power allocation is computed by the water-filling algorithm. The main drawback of this study is the assumption of perfect SI cancellation. Thus, the SI is treated as background noise which is not practical.

1.3 Research Objectives and Contributions

The main objective of the research studied in this thesis is to develop the algorithms for allocating the resources in FD OFDMA networks in order to maximize the system sum-rate. Different approaches to the optimization problem of this system are examined as well. Moreover, the effects of various factors on the system's output such as the SI cancellation parameters or the maximum power constraints are also considered in this research. Specifically, the contributions of this thesis are described in the following.

Recent works on FD wireless communication systems only consider the FD transmission enabled at the BS while the nodes still operates in HD mode or assume perfect SI cancellation, thus chapter 3 of this thesis examines a more general case of the FD networks. The system model studied in this thesis is a single cell OFDMA network. All terminals (base station and users) have FD capability and they can all switch between FD transmission mode or HD transmission mode. Our objective is to maximize the total rate of the network by jointly optimizing the subcarrier assignment and power allocation. Since imperfect SI cancellation is considered in our work, the SI in our thesis is modelled as monomial form of transmission power (eq. (8) in [36]). First, we formulate the considered joint optimization problem as nonconvex mixed integer programming, which is NP-hard in general. Then two approaches are proposed to solve this problem along with two fast greedy algorithms in order to demonstrate the significant gains of our proposed design. The main contributions of this thesis can be summarized as follows:

- A comprehensive optimization model is proposed to optimize the sum-rate of our single cell FD OFDMA network. Every terminal in the system is capable of FD transmission. Additionally, to further increase the flexiblity of the system, the users and BS can switch between FD and HD mode whichever offers the best sum-rate. The effect of transmission power on the SI is also considered in our system model.

- Two methods were developed to solve the nonconvex mixed integer problem formulated from our system model. In the first proposed algorithm, the SA is found by using the bipartite matching method. The weights matrix for this method is created by a fast greedy allocation which finds the maximum number of links in a subcarrier that offers the best sum-rate. Then from the given SA, we transform the PA problem into a concave function by using the successive convex approximation method [27, 37].

- In the second approach, we developed an iterative algorithm to solve this problem. First, the SA variables are relaxed from integer values into real values and then in each iteration, they are slowly updated by a gradient method [38]. Then with the updated SA variables, the PA problem is solved by the successive convex approximation method.
- Simulation results are presented to demonstrate the effectiveness of our proposed algorithms. The impacts of different parameters on the outcomes of the resource allocation method are also considered. The simulation results also show the convergence of our iterative algorithm. Moreover, it can be observed that the performance of the proposed methods is much better than the fast greedy approaches. Additionally, the system sum-rate for FD transmission methods is better than HD method in most of the cases.

1.4 Thesis Outline

The rest of this thesis is organized as follows. Chapter 2 contains the relevant background to this thesis including the basic optimization techniques including linear programming, and some popular optimization as well as the basic of FD communication model. Chapter 3 presents the system model and mathematical formulation of the joint optimization problem for resource allocation in the single cell FD OFDMA network. The proposed algorithms to solve this problem are also introduced along with the simulation results to demonstrate the algorithms's performance. Finally, chapter 4 concludes the thesis by providing a brief summary of the accomplished work and outlining some future research directions.

Chapter 2

Background

This chapter presents the general background on the mathematical optimization techniques used in this thesis including linear programming, mixed integer linear programming, proximal minimization algorithm and Hungarian method. We also introduce basic concepts on the topic of resource allocation for FD OFDMA systems and its challenges.

2.1 Optimization Techniques

2.1.1 Basic Concepts

An optimization problem can be expressed in the following standard form [39]:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq 0,\ i = 1, \ldots, m \\ & h_i(x) = 0,\ i = 1, \ldots, p \end{aligned} \tag{2.1}$$

where $x \in \mathbb{R}^n$ is the optimization variable, $f_0 : \mathbb{R}^n \to \mathbb{R}$ is the objective or cost function, $f_i : \mathbb{R}^n \to \mathbb{R}, i = 1, \ldots, m$ are inequality constraint functions, $h_i : \mathbb{R}^n \to \mathbb{R}, i = 1, \ldots, p$ are equality constraint functions. The set of x that satisfies all constraints of problem (2.1) is called the feasible set. If the feasible set is empty, the problem is infeasible. The optimal value p^* of the problem is defined as follows:

$$p^* = \inf\{f_0(x) | h_i(x), i = 1, \ldots, p, f_i(x) \leq 0, i = 1, \ldots, m\} \tag{2.2}$$

Note that if the problem is infeasible, $p^* = \infty$ and if the problem is unbounded below $p^* = \infty$.

2.1.2 Linear Programming and Mixed Integer Linear Programming

A linear programming (or a linear programming problem) is a special case of the general optimization problem in which the objective function and all constraint functions are in linear form. In general, a linear programming (LP) has the following form

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & \boldsymbol{c'}x + e \\ \text{subject to} \quad & \boldsymbol{A}x \le \boldsymbol{b} \\ & \boldsymbol{C}x \le \boldsymbol{d} \end{aligned} \tag{2.3}$$

where

- $x \in \mathbb{R}^n$, $\boldsymbol{c'} \in \mathbb{R}^n$, $\boldsymbol{b} \in \mathbb{R}^n$, $\boldsymbol{d} \in \mathbb{R}^n$,
- Matrices $\boldsymbol{A}$ and $\boldsymbol{C}$ have appropriate sizes.

If some or all variables x_i (i.e., some or all elements in vector $x = \{x_1, x_2, \ldots, x_n\}$) must be integer values, our optimization problem becomes a mixed integer linear programming problem (MILP).

Note that a function involving absolute operations is essentially a nonlinear function. Nevertheless, if the objective function involves the absolute values of some variables, the problem can stil be easily transformed to an equivalent linear programming form by the use of some auxiliary variables. For instance, let us consider the following optimization problem

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & |\boldsymbol{c'}x + d| \\ \text{subject to} \quad & \boldsymbol{A}x \le \boldsymbol{b} \end{aligned} \tag{2.4}$$

where $x \in \mathbb{R}^n$. As we can see, the objective function is nonlinear. However, the problem can be transformed into the following LP

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & t \\ \text{subject to} \quad & \boldsymbol{A}x \leq \boldsymbol{b} \\ & \boldsymbol{c'}x + d \leq t \\ & -\boldsymbol{c'}x - d \leq t. \end{aligned} \tag{2.5}$$

which can be solved by many algorithms such as the ellipsoid method or the interior point methods.

2.1.3 Convex Optimization Problem

A set S is convex if it satisfies the following condition [40]

$$\alpha x + \beta y \in S, \forall x, y \in S, \tag{2.6}$$

such that $\alpha + \beta = 1, \alpha > 0, \beta > 0$.

Then a function $f : \mathbb{R}^n \to \mathbb{R}$ is convex if the domain $\mathcal{D}$ of f is convex set and f satisfies

$$f_i(\alpha x + \beta y) \leq \alpha f_i(x) + \beta f_i(y) \tag{2.7}$$

for all $x, y \in \mathbb{R}^n$ and all $\alpha, \beta \in \mathbb{R}$, with $\alpha + \beta = 1$, $\alpha > 0$, $\beta > 0$.

A convex optimization problem has the following form

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f_0(x) \\ \text{subject to} \quad & f_i(x) \leq 0,\ i = 1, \ldots, m \end{aligned} \tag{2.8}$$

where the functions $f_0, \ldots, f_m : \mathbb{R}^n \to \mathbb{R}$ are convex.

2.1.4 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 problem 2.1 has the form

$$\mathcal{L}(x, \lambda, \nu) = f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x) \tag{2.9}$$

where λ_i and ν_i are the Lagrangian 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 follows

$$g(\lambda, \nu) = \inf_{x \in \mathcal{D}} \mathcal{L}(x, \lambda, \nu) = \inf_{x \in \mathcal{D}} \left(f_0(x) + \sum_{i=1}^{m} \lambda_i f_i(x) + \sum_{i=1}^{p} \nu_i h_i(x) \right) \tag{2.10}$$

The *Lagrange dual problem* is then defined as

$$\begin{aligned} \underset{\lambda, \nu}{\text{maximize}} \quad & g(\lambda, \nu) \\ \text{subject to} \quad & \lambda \geq 0. \end{aligned} \tag{2.11}$$

Problem 2.1 is the primal problem. The optimal value of 2.11 is denoted by p^* and the difference $p^* - d^*$ is referred to as optimal duality gap. When $p^* = d^*$, the optimal duality gap is zero $p^* = d^*$ and the problem has strong duality.

2.1.5 Karush-Kuhn-Tucker Conditions

Let x^* and $(\lambda^*; \nu^*)$ be the primal and dual optimal solution with strong duality condition. Then they will satisfy the KKT conditions which are expressed as follows

$$\begin{aligned} & f_i(x^*) \leq 0, && \forall i = 1, \ldots, m \\ & h_i(x^*) = 0, && \forall i = 1, \ldots, p \\ & \lambda_i^* \geq 0, && \forall i = 1, \ldots, m \\ & \lambda_i^* f_i(x^*) = 0, && \forall i = 1, \ldots, m \\ & \nabla f_0(x^*) + \sum_{i=1}^{m} \lambda_i^* \nabla f_i(x^*) + \sum_{i=1}^{p} \nu_i^* \nabla h_i(x^*) = 0 \end{aligned} \tag{2.12}$$

where ∇f is the gradient of f.

Theorem 1: the conditions 2.12 are sufficient conditions to obtain an optimal solution for convex optimization problem.

It means that any points x^* and $(\lambda^*; \nu^*)$ satisfy the KKT conditions are primal and dual optimal solutions.

2.1.6 Resource Allocation Algorithms

In this section, we provide the background on the methods that are used in our proposed gradient algorithm and bipartite matching algorithm.

2.1.6.1 Proximal Minimization Algorithm

The classical proximal minimization algorithm [41] obtains a solution of the problem $min_{x \in \mathcal{X}} f(\mathbf{x})$ by solving an equivalent problem

$$\underset{\mathbf{x}\in\mathcal{X},\mathbf{y}\in\mathcal{X}}{\text{minimize}} f(\mathbf{x}) + \frac{1}{2c}||\mathbf{x}-\mathbf{y}||_2^2 \tag{2.13}$$

where $f(\cdot)$ is a convex function, $\mathcal{X}$ is a closed convex set, and $c > 0$ is a scalar parameter. The equivalent problem is attractive in that it is strongly convex in both x and y (but not jointly) so long as $f(x)$ is convex. This problem can be solved by performing the following two steps in an alternating fashion

$$\mathbf{x}^{r+1} = \arg\min_{\mathbf{x}\in\mathcal{X}} \left\{ f(\mathbf{x}) + \frac{1}{2c}||\mathbf{x}-\mathbf{y}^r||_2^2 \right\} \tag{2.14}$$

$$\mathbf{y}^{r+1} = \mathbf{x}^{r+1}. \tag{2.15}$$

Equivalently, the iteration (2.14) and (2.15) can be written as

$$\mathbf{x}^{r+1} = \arg\min_{\mathbf{x}\in\mathcal{X}} \left\{ f(\mathbf{x}) + \frac{1}{2c}||\mathbf{x}-\mathbf{x}^r||_2^2 \right\}. \tag{2.16}$$

Let $u(\mathbf{x}, \mathbf{x}^r) \triangleq f(\mathbf{x}) + \frac{1}{2c}||\mathbf{x}-\mathbf{x}^r||_2^2$, then for all $\mathbf{x}, \mathbf{x}^r \in \mathcal{X}$, $u(\mathbf{x}, \mathbf{x}^r)$ serves as an upper bound for the function $f(\mathbf{x})$ and every limit point of the iterates generated by the algorithm is a stationary point of the problem $min_{x\in\mathcal{X}} f(\mathbf{x})$ [38].

2.1.6.2 The Hungarian Method

We now introduce the Hungarian method for the maximum-weight matching problem [42].

Let $G = (V, E)$ be a bipartite graph, with colour classes A and B, and let $w : E \to \mathbb{Q}$ be a weight function. The integer linear programming formulation of the maximum weight matching problem has the following form:

$$\begin{aligned} \max_{x} \quad & \sum_{(a,b)} w(a,b)x(a,b) \\ \text{subject to} \quad & \sum_{(a)} x(a,b) = 1, \forall a \in A \\ & \sum_{(b)} x(a,b) = 1, \forall b \in B \\ & x(a,b) \in \{0,1\}, \forall a \in A, \forall b \in B. \end{aligned} \tag{2.17}$$

We start with matching $M = \emptyset$. If we have found a matching M, let D_M be the directed graph obtained from G by orienting each edge e in M from A to B, with length $l_e := w_e$, and orienting each edge e not in M from B to A, with length $l_e := -w_e$. Let B_M and A_M be the set of vertices in B and A, respectively, missed by M. If there is a $B_M - A_M$ path, find a shortest such path, P say, and reset $M' := M \Delta EP$.

The algorithm iterates until no $B_M - A_M$ path exists in D_M (whence M is a maximum-size matching). The maximum-weight matching among the matchings found, has maximum weight among all matchings.

2.2 Resource Allocation for OFDMA networks

In this section, we provide the background on the resource allocation topic for FD OFDMA communication systems [15].

2.2.1 Basics of FD Communication

We consider two nodes with a transmit and receive antenna at each node. The data can be transmitted and received simultaneously on the same frequency band and time slot. Therefore, the signal leakage from the transmit RF unit to the receive RF unit can induce severe SI. The effect of SI can be reduce by techniques such as antenna cancellation or analog and digital signal processing.

The difference in power between the SI and the received signal can vary between 50-110 dB depends on the placement of the transmit and receive antenna. As a result, the SINR is greatly reduced from the effect of the SI on the received signal. Thus, the SI needs to be weakened by the analog SI cancellation before the AD conversion process. Then, the output AD conversion can be further improved with the digital SI cancellation. Nevertheless, in reality, the SI can never be mitigated completely because of practical constraints. Therefore, the signals received at each node are a combination of the signal transmitted by the other source, the residual self-interference(RSI), and the noise and can be modeled as follows

$$y_1 = \sqrt{p_2} h_{21} x_2 + \sqrt{p_1} \tilde{h}_{11} x_1 + n_1, \tag{2.18}$$

where p_1 and p_2 represent the transmit power at each node, h_{21} denotes the communication channel from node 2 to node 1, $\tilde{h}_{11}$ represents the interference channel, and n_1 denotes the noise term. Thus, the instantaneous received SINR of node 1 can be calculated as

$$\gamma_1 = \frac{|h_{21}|^2 p_2}{|\tilde{h}_{11}|^2 p_1 + N_0}. \tag{2.19}$$

As can be seen from 2.19, the instantaneous SINR is inversely proportional to the RSI. The values of h_{21}, h_{11}, p_2 and p_1 can greatly affect the SINR, and therefore will alter the system performance significantly, On the other hand, in traditional HD communication networks, the system performance is only affected by the transmit side. Thus, optimal resource allocation is an effective way to minimize the the effects of RSI for FD communication systems.

OFDMA is a popular method employed in many current wireless and cellular communication systems. The efficient resource allocation in OFDMA FD networks has recently gained new research interest. In FD OFDMA cellular networks, a transceiver pair formed by a transmit (TX) and receive (RX) node needs to be chosen properly since the users simultaneously communicate with the FD BS over the same subset of subcarriers. Thus, the receive user will receive co-channel interference caused by the TX user, the intensity of the interference is inversely proportional to the mutual distance between the TX and RX users of each pair. In order to achieve optimal system sum-rate performance, the pairing between users, subcarrier assignment and power allocation need to be perform carefully. Since the problem of subcarrier assignment and user pairing is a combinatorial optimization problem, resource allocation in such an FD OFDMA network can be very challenging.

2.2.2 Resource Allocation in FD OFDMA System

In this section, we introduce the main resource allocation problems for FD communication systems. Since the system performance depends greatly on the RSI, the key resource allocation problems for FD OFDMA communications systems can be summarized below.

- *Mode Switch*: Because the SI can never be removed completely, so in some scenarios, HD transmission might have a better performance than FD transmission. Therefore, it is essential to understand the performance of these two transmission modes in order to identify the conditions for which the system performance is maximized. Thus, adaptive mode switching between the FD and HD modes based on the RSI and channel conditions is essential to achieve optimal sum-rate.

- *Subcarrier Assignment*: In an FD OFDMA system consisting of one FD BS with S subcarriers, N_U uplink users, and N_D downlink users, pairing uplink and downlink users, and allocating subcarriers across these user pairs to optimize network performance is a challenging problem. The RSI and the co-channel interference between the uplink and downlink users must be considered in order to allocate subcarrier from different subsets to different users. This is significantly different from the traditional subcarrier allocation problem in normal HD OFDMA system.

- *Power Allocation*: In FD OFDMA network with one BS and multiple users, the transmit power at the BS can be allocated with by splitting the power among all the subcarriers for different user pairs. However, power allocation at the user side needs to consider the inter-user distance among the transmit-receiver user pair. Therefor, the power allocation problem in the FD-OFDMA system is more complicated since it depends on many factors, which requires multidimensional optimization for the BS and the users.

2.3 Summary

In this chapter, we have introduced some basic concepts of mathematical optimization problem which are linear programming, convex problem. The proximal minimization algorithm and Hungarian method were also discussed in this chapter. Then, the relevant technical background on resource allocation in FD OFDMA networks and its challenge were considered as well.

Chapter 3

Resource Allocation for Full-Duplex OFDMA Wireless Cellular Networks

In this chapter, the problem for joint subcarrier assignment and power allocation for a FD OFDMA network is considered. The chapter begins with a description of our system model and its mathematical formulation of the underlying optimization problem. Then, we present different approaches to solve the problem. Finally, the numerical results for all of the introduced algorithms are provided to show the effectiveness of our proposed methods.

3.1 System Model and Problem Formulation

3.1.1 System Model

We consider a single cell OFDMA network consisting of one base station (BS) and N mobile nodes all equipped with FD communication capability. Therefore, the BS and all the nodes are able to transmit and receive signals simultaneously on any subcarrier (SC). There are S orthogonal SCs in the considered frequency band. Let $\mathcal{N} = \{1, 2, ..., N\}$ and $\mathcal{S} = \{1, 2, ..., S\}$ denote the set of nodes and the set of SCs, respectively. In this model, we also assume that each SC can be assigned to at most one user for UL transmission and also at most one user for DL transmission. The SA pattern for the UL and DL sides is defined by the binary vectors $\vec{X}^{\mathsf{U}} \triangleq \{x^{\mathsf{U}}_{n,s}\}_{n\in\mathcal{N},s\in\mathcal{S}}$ and $\vec{X}^{\mathsf{D}} \triangleq \{x^{\mathsf{D}}_{n,s}\}_{n\in\mathcal{N},s\in\mathcal{S}}$, respectively, where each component of

$x^{\mathsf{U}}_{n,s}$'s and $x^{\mathsf{U}}_{n,s}$'s is defined as

$$x^{\mathsf{U}}_{n,s}(\text{or } x^{\mathsf{D}}_{n,s})=\begin{cases}1 \text{ if user } n \text{ uses SC } s \text{ for UL (or DL)},\\ \\ 0 \text{ otherwise.}\end{cases} \tag{3.1}$$

Let $p^{\mathsf{U}}_{n,s}$ denote the UL power allocated to SC s by node n and $p^{\mathsf{D}}_{n,s}$ denote the DL power allocated to SC s for node n by BS. PA vector is defined as $\vec{P} \triangleq \{\vec{p}^{\mathsf{U}}_s, \vec{p}^{\mathsf{D}}_s\}_{s\in\mathcal{S}}$ where $\vec{p}^{\mathsf{U}}_s$ and $\vec{p}^{\mathsf{D}}_s$ are the uplink and downlink power vectors for SC s, respectively. The perfect channel state information (CSI) for each node and SC is assumed to be known by the BS. We can now start analyzing the rates achieved by all terminals in our system in order to define our problem.

3.1.1.1 Rate achieved at the base station

Because of the FD transmission, the received signal at BS over SC s is interfered by the DL transmitted signal from BS over that SC. Since the interference cancellation is not perfect, it will not be able to completely negate the interference. Thus, there exists residual self-interference in the SC. According to [36], the self-interference at the BS from DL transmission corresponding to SC s can be formulated as

$$I^{\mathsf{U}}_s\left(\vec{x}^{\mathsf{D}}_s, \vec{p}^{\mathsf{D}}_s\right) = \sum_{n\in\mathcal{N}} x^{\mathsf{D}}_{n,s}\epsilon\left(p^{\mathsf{D}}_{n,s}\right)^{\theta}, \tag{3.2}$$

where $\vec{x}^{\mathsf{D}}_s = \{x^{\mathsf{D}}_{n,s}\}_{n\in\mathcal{N}}$ is the DL SA vector for SC s, ϵ and θ are fixed scaling factors which captures the quality of the SI cancellation techniques. When $\theta = 1$, the self-interference power is a linear function of the transmitted power [17]. When $\theta = 0$, the self-interference is a constant regardless of the transmitted power and thus can be treated as background noise [18]. Then, the rate achieved at the base station for the user n on the UL transmission over SC s can be computed as

$$R^{\mathsf{U}}_{n,s}\left(\vec{X}, \vec{P}\right) = \log\left(1 + \frac{x^{\mathsf{U}}_{n,s}G^{\mathsf{U}}_{n,s}p^{\mathsf{U}}_{n,s}}{I^{\mathsf{U}}_s\left(\vec{x}^{\mathsf{D}}_s, \vec{p}^{\mathsf{D}}_s\right) + N_0}\right), \tag{3.3}$$

where $G^{\mathsf{U}}_{n,s}$ is UL channel gain between node n and the BS, and N_0 is the receiver noise power.

3.1.1.2 Rate achieved at the users

There are two cases which can happen when the user n is assigned SC s over DL transmission. In the first case, user n also uses the same SC s for UL transmission. Therefore, this UL transmission creates self-interference and can be calculated as $\epsilon\left(p^{\mathsf{U}}_{n,s}\right)^{\theta}$. The second case is that SC s is given to user j for UL transmission. Then, in this case the UL transmission from user j creates the cross-interference for the received DL signal of user n over SC s, and this interference can be calculated as

$$I^{\mathsf{cr}}_{j,n,s}\left(\vec{x}^{\mathsf{U}}_{s},\vec{p}^{\mathsf{U}}_{s}\right)=x^{\mathsf{U}}_{j,s}G_{j,n,s}p^{\mathsf{U}}_{j,s}, \tag{3.4}$$

where $G_{n,j,s}$ is the interference channel gain from user n to user j over SC s and $\vec{x}^{\mathsf{U}}_{s}=\{x^{\mathsf{U}}_{n,s}\}_{n\in\mathcal{N}}$ is UL SA vector for SC s. Generally, the interference on the received signal of user n over SC s can be summarized as follows.

$$I^{\mathsf{D}}_{n,s}\left(\vec{x}^{\mathsf{U}}_{s},\vec{p}^{\mathsf{U}}_{s}\right)=\sum_{j\in\mathcal{N}/n}x^{\mathsf{U}}_{j,s}G_{j,n,s}p^{\mathsf{U}}_{j,s}+x^{\mathsf{U}}_{n,s}\epsilon\left(p^{\mathsf{U}}_{n,s}\right)^{\theta}. \tag{3.5}$$

Then, the rate achieved by the user n on the DL transmission over SC s can be computed as

$$R^{\mathsf{D}}_{n,s}\left(\vec{X},\vec{P}\right)=\log\left(1+\frac{x^{\mathsf{D}}_{n,s}G^{\mathsf{D}}_{n,s}p^{\mathsf{D}}_{n,s}}{I^{\mathsf{D}}_{n,s}\left(\vec{x}^{\mathsf{U}}_{s},\vec{p}^{\mathsf{U}}_{s}\right)+N_0}\right). \tag{3.6}$$

Overall, Fig.3.1 shows the model of our FD system and the possible cases of users pairing that can happen in our model.

3.1.2 Problem Formulation

In this section, we formulate the joint FD SA and PA problem based on the above analysis. This problem aims to calculate the SA for users in DL ans UL transmission as well as the corresponding power transmission for each link in order to maximize the total rate of the

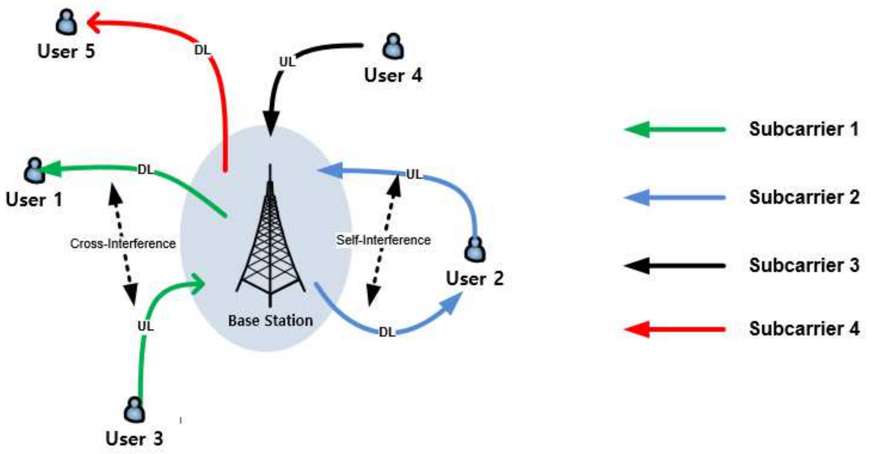

Figure 3.1: System Model of the FD OFDMA network.

network. From to these objectives, our problem can be formulated as

$$\max_{\vec{X},\vec{P}} R_{\mathsf{total}} = \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} R^{\mathsf{U}}_{n,s}\left(\vec{X},\vec{P}\right) + R^{\mathsf{D}}_{n,s}\left(\vec{X},\vec{P}\right) \tag{3.7a}$$

$$\text{s.t.} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} p^{\mathsf{D}}_{n,s} \le P_{\mathsf{BS}}, \tag{3.7b}$$

$$\sum_{s\in\mathcal{S}} p^{\mathsf{U}}_{n,s} \le P_n,\ \forall n\in\mathcal{N}, \tag{3.7c}$$

$$\sum_{n\in\mathcal{N}} x^{\mathsf{U}}_{n,s} \le 1 \text{ and } \sum_{n\in\mathcal{N}} x^{\mathsf{D}}_{n,s} \le 1,\ \forall s\in\mathcal{S}, \tag{3.7d}$$

$$x^{\mathsf{U}}_{n,s}, x^{\mathsf{D}}_{n,s} \in \{0,1\},\ \forall n\in\mathcal{N},\ \forall s\in\mathcal{S}. \tag{3.7e}$$

In this optimization problem, P_{BS} and P_n denote the maximum transmission power budget that BS and user n can use, respectively. The first two constraints (3.7b) and (3.7c) are the maximum power budget for the BS and each node. The constraints (3.7d) impose the assignment of SC s to at most one user for UL or DL transmissions. It can easily be seen that the optimization problem (3.7) is a mixed integer programming, which is NP-hard in general and requires exponential complexity to be solved. Inspired by a recent work in PA and SA [27], we propose an iterative algorithm in the subsequent sections to find the local optimal solution to problem (3.7). In the next section, we are going to introduce two approaches to our problem. The first method is the bipartite matching algorithm with the weights calculated using the result of the fast greedy algorithm. The second approach is to solve our integer non-convex problem using the gradient method by relaxing the integer variables and updating them with their gradients iteratively to find the solution. The basic model of our algorithms is demonstrated in Fig. 3.2.

3.2 SA with Given PA or Uniform Power Allocation

First, we consider the SA problem when the PA is known. Since the SA variables are integer, we propose three methods to solve our problem: the greedy allocation, the bipartite matching and the gradient update method.

3.2.1 Greedy Allocation

In this section, we introduce a fast greedy allocation algorithm for the SA problem. In this algorithm, each subcarrier will choose the group of nodes in both UL and DL transmission that offers the best rate, the constraint of maximum one UL and one DL transmission per subcarrier is ignored in this algorithm. Let $\mathcal{U}_s^{\mathsf{D}}$ and $\mathcal{U}_s^{\mathsf{U}}$ be the list of nodes assigned to subcarrier s for DL and UL, respectively. The rate of subcarrier s will be the sum of its users's rate. We will start analyzing the interference at each case of receiving terminal.

Interference at base station At the base station, there are two sources of interference: from a node in UL mode or the SI from the base station transmitting in DL mode. Thus, the interference can be given as

$$I_{j,s}^{\prime\mathsf{U}}\left(\vec{P}\right) = \begin{cases} \epsilon\left(p_{j,s}^{\mathsf{D}}\right)^{\theta}, j \in \mathcal{U}_s^{\mathsf{D}}, s \in \mathcal{S}, \\ \\ G_{j,s}^{\mathsf{U}} p_{j,s}^{\mathsf{U}}, j \in \mathcal{U}_s^{\mathsf{U}}, s \in \mathcal{S}. \end{cases} \tag{3.8}$$

Interference at node At the user, there are three sources of interference: from the base station broadcasting to another user in the same subcarrier, from another user in UL mode

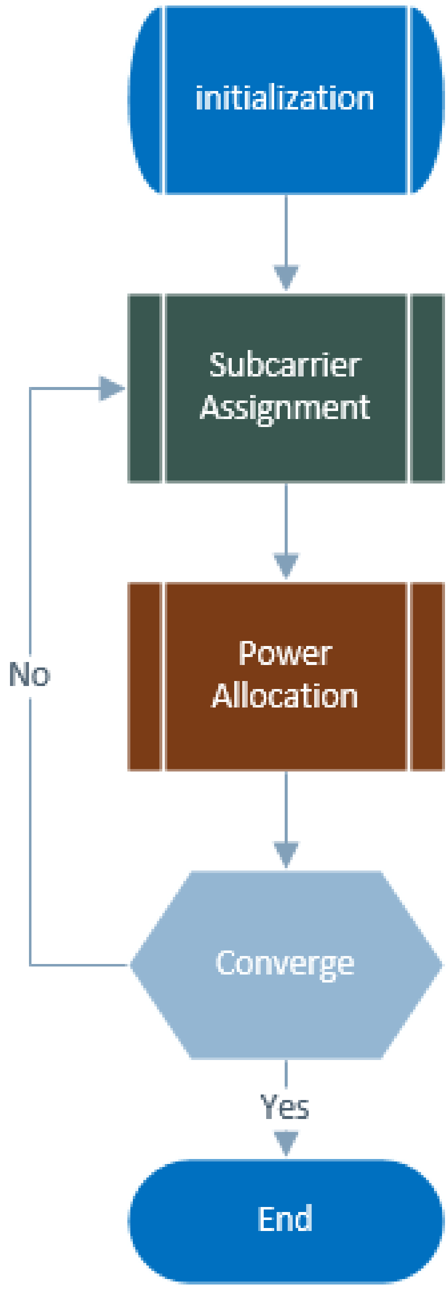

Figure 3.2: Block diagram of our algorithms.

or the SI of that user in UL mode. Thus, the interference can be given as

$$I'^{\mathsf{D}}_{j,n,s}\left(\vec{P}\right) = \begin{cases} G_{j,n,s}p^{\mathsf{U}}_{j,s}, j \in \mathcal{U}^{\mathsf{U}}_s, n \in \mathcal{U}^{\mathsf{D}}_s, s \in \mathcal{S}, j \neq n, \\ \\ G^{\mathsf{D}}_{j,s}p^{\mathsf{D}}_{j,s}, j \in \mathcal{U}^{\mathsf{D}}_s, s \in \mathcal{S}, \\ \\ \epsilon\left(p^{\mathsf{U}}_{j,s}\right)^{\theta}, j \in \mathcal{U}^{\mathsf{U}}_s, s \in \mathcal{S}. \end{cases} \tag{3.9}$$

Rate at subcarrier From the above interference, the rate of a subcarrier s can be calculated as follows:

$$R_s(\vec{P}) = \sum_{n \in \mathcal{U}^{\mathsf{U}}_s} log(1 + \frac{G^{\mathsf{U}}_{n,s}p^{\mathsf{U}}_{n,s}}{\sum_{j \in \mathcal{U}^{\mathsf{U}}_s} I'^{\mathsf{U}}_{j,s} + N_0}) + \sum_{n \in \mathcal{U}^{\mathsf{D}}_s} log(1 + \frac{G^{\mathsf{D}}_{n,s}p^{\mathsf{D}}_{n,s}}{\sum_{j' \in \mathcal{U}^{\mathsf{D}}_s} I'^{\mathsf{D}}_{j',n,s} + N_0}). \tag{3.10}$$

The algorithm uses uniform power allocation for all assigned nodes and subcarriers. The details of the greedy allocation are described in Algorithm 1.

Algorithm 1 GREEDY ALLOCATION ALGORITHM

```
for each subcarrier s in S do
  U_s^D, U_s^U ← ∅
  Initialize iteration iteration i = 0
  repeat
    for each n ∈ N in UL or DL transmission do
      if n ∉ U_s^D or n ∉ U_s^D then
        Assume n is added to s, apply uniform power allocation to all nodes in U^D and
        U^U.
        Calculate the rate of s using (3.10).
      end if
    end for
    Let n* be the node which offers the best rate.
    U_s^D ← n* if n* is in DL, otherwise U_s^U ← n*
    Update iteration iteration i = i + 1
  until The rate of subcarrier s in current iteration is less than the rate in previous
  iteration R_s^i < R_s^{i-1}
end for
update X⃗ using U^U and U^D.
```

3.2.2 Bipartite Matching Allocation

Since each subcarrier can have at most one DL transmission and UL transmission for N nodes, there will be N^2 possible pairs of users in FD mode that can happen. As the subcarriers can also be used in HD mode, we will have another $2N$ cases to consider. Thus, we define a $K \times K$ matrix M where $K = N^2 + 2N$. The rows $\{1, 2, .., N^2\}$ in the matrix represent the pair of UL and DL in FD mode and rows $\{N^2 + 1, ..., N^2 + 2N\}$ are in HD mode. The columns $\{1, ..., S\}$ represent the subcarriers and the rest of them are dummy in order for the matrix to be square. The value in each matrix cell is the rate obtained when the pair of nodes (n, j) are assigned to subcarrier s.

For simplicity, new power variables q_s^{U} and q_s^{D} are introduced to represent the transmission power for all users on each SC for UL side and DL side, respectively. The new PA vector is defined as $\vec{Q}$ where $\vec{Q} \triangleq \{\vec{q}_s^{\mathsf{U}}, \vec{q}_s^{\mathsf{D}}\}_{s\in\mathcal{S}}$. The relation between q_s^{U} and $p_{n,s}^{\mathsf{U}}$, q_s^{D} and $p_{n,s}^{\mathsf{D}}$ can be given as

$$q_s^{\mathsf{U}} = \sum_{n\in\mathcal{N}} x_{n,s}^{\mathsf{U}} p_{n,s}^{\mathsf{U}}, \quad q_s^{\mathsf{D}} = \sum_{n\in\mathcal{N}} x_{n,s}^{\mathsf{D}} p_{n,s}^{\mathsf{D}}. \tag{3.11}$$

Thus, the value of the cell on row a^{th}, column s^{th} with $a \in \{1, ..., N^2\}$ and $s \in \mathcal{S}$ can be calculated as

$$W_{a,s}\left(q_s^{\mathsf{D}}, q_s^{\mathsf{U}}\right) = \log\left(1 + \frac{q_s^{\mathsf{U}} G_{j,s}^{\mathsf{U}}}{\epsilon\left(q_s^{\mathsf{D}}\right)^{\theta} + N_0}\right) + \log\left(1 + \frac{G_{n,s}^{\mathsf{D}} q_s^{\mathsf{D}}}{G_{j,n,s} q_s^{\mathsf{U}} + \epsilon_s^{\mathsf{U}}\left(q_s^{\mathsf{U}}\right)^{\theta} + N_0}\right), \tag{3.12}$$

where $n = \lceil a/N \rceil$ and $j = a - \lfloor a/N \rfloor N$.

For rows $\{N^2 + 1, ..., N^2 + N\}$ which are for DL transmission in HD mode, the values of the cell in columns $\{1, ..., S\}$ are

$$W_{a,s}\left(q_s^{\mathsf{D}}\right) = \log\left(1 + \frac{G_{n,s}^{\mathsf{D}} q_s^{\mathsf{D}}}{N_0}\right), \tag{3.13}$$

where $n = a - N^2$.

Rows $\{N^2 + N + 1, ..., N^2 + 2N\}$ are the case of UL transmission in HD mode. The cell's values in columns $\{1, ..., S\}$ are

$$W_{a,s}\left(q_s^{\mathsf{U}}\right) = \log\left(1 + \frac{G_{n,s}^{\mathsf{U}} q_s^{\mathsf{U}}}{N_0}\right), \tag{3.14}$$

where $n = a - N^2$. The rest of matrix M will be filled with 0. Fig. 3.3 shows the structure of our matching weight matrix.

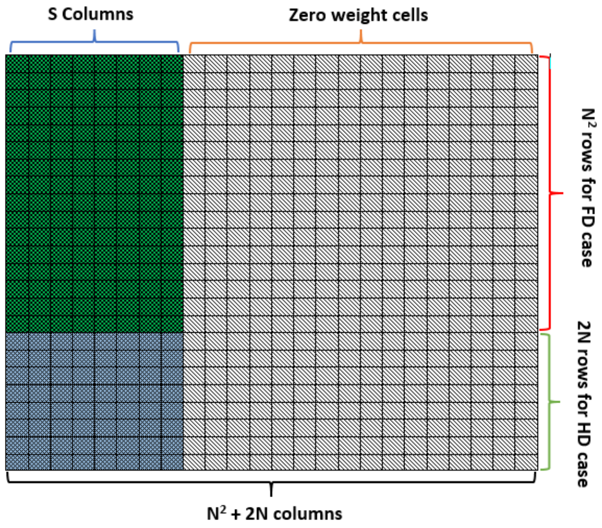

Figure 3.3: Structure of the matching weight matrix.

Since M is a square matrix with the values in each cell consider as "weight" for a sub-carrier s and we want to find the combination that offers the maximum rate, hence it is an assignment problem. Let $\tilde{x}_{a,s} \in \vec{\tilde{X}}$ be the binary assignment variable for our weight matrix M, then our bipartite matching based SA problem can be formulated as follows:

$$\max_{\vec{\tilde{X}}} \sum_{a \in \mathcal{K}} \sum_{s \in \mathcal{S}} W_{a,s} \tilde{x}_{a,s} \tag{3.15}$$

$$\sum_{a \in \mathcal{K}} \tilde{x}_{a,s} = 1, \ \forall s \in \mathcal{S}, \tag{3.16}$$

$$\tilde{x}_{a,s} \in \{0, 1\}, \ \forall a \in \mathcal{K}, \ \forall s \in \mathcal{S}. \tag{3.17}$$

The Kuhn-Munkres algorithm can be applied to find the optimal solution of problem (3.15)-(3.17) in polynomial time.

3.2.3 Gradient Update Method

This section investigates the method to find a good SA for all users with given PA over all SCs for downstream and upstream by updating the SA variables using the gradient method. Assume $\vec{Q}$ is given, we replace the quadratic terms $x^{\mathsf{D}}_{n,s} x^{\mathsf{U}}_{j,s}$ in $\epsilon^{\mathsf{U}}_s(\vec{X})$ by the following binary variables

$$y_{n,j,s} = x^{\mathsf{D}}_{n,s} x^{\mathsf{U}}_{j,s}, \ \ \forall n, j \in \mathcal{N}. \tag{3.18}$$

As can be observed, $y_{n,j,s} = 1$ if SC s is assigned to user n in DL and to user j in UL, and $y_{n,j,s} = 0$, otherwise. When $y_{n,j,s} = 1$, the rate achieved over SC s for given $\vec{Q}$ can be calculated as

$$R_{n,j,s} = \log\left(1 + \frac{G^{\mathsf{U}}_{j,s} q^{\mathsf{U}}_s}{\epsilon\left(q^{\mathsf{D}}_s\right)^{\theta} + N_0}\right) + \log\left(1 + \frac{G^{\mathsf{D}}_{n,s} q^{\mathsf{D}}_s}{I'^{\mathsf{D}}_{\vec{Q},s}(n,j) + N_0}\right), \tag{3.19}$$

where

$$I'^{\mathsf{D}}_{\vec{Q},s}(n,j) = \begin{cases} \epsilon\left(q^{\mathsf{U}}_s\right)^{\theta} & \text{if } n = j, \\ G_{j,n,s} q^{\mathsf{U}}_s & \text{if } n \neq j. \end{cases} \tag{3.20}$$

Given the values of q_s^U and q_s^D, we optimize the allocation $y_{n,j,s}$:

$$\max_{\vec{Y}} \; R_{\vec{Q}}(\vec{Y}) = \sum_{\forall(n,j)} \sum_{s \in \mathcal{S}} R_{n,j,s} y_{n,j,s} \tag{3.21a}$$

$$\text{s.t.} \; \sum_{n \in \mathcal{N}} \sum_{s \in \mathcal{S}} q^{\mathsf{U}}_s y_{n,j,s} \leq P_j, \;\; \forall j \in \mathcal{N}, \tag{3.21b}$$

$$\sum_{\forall(n,j)} y_{n,j,s} \leq 1, \;\; s \in \mathcal{S}, \tag{3.21c}$$

$$y_{n,j,s} \in \{0,1\}, \; \forall(n,j), \; \forall s \in \mathcal{S}, \tag{3.21d}$$

where $\vec{Y}$ represents the vector generated from all variables $y_{n,j,s}$'s. While problem (3.21) is a nonconvex integer programming, its global optimization can be found. By relaxing the last constraint (3.21d) into $0 \leq y_{n,j,s} \leq 1$, the problem (3.21) becomes a linear programming (LP) in $y_{n,j,s}$'s, whose optimal solution can be found efficiently by standard convex optimization techniques. Interesting, as shown in [38] the obtained optimal solution of this LP lies at a vertex where $y_{n,j,s}$'s will be either 0 and 1. Thus, given $\vec{Q}$, as well as $R_{n,j,s}$'s, solving the LP will result in the optimal SA for each user. However, once $y_{n,j,s}$'s take the value of 0 or 1, the SA for each user may be trapped in a local optimal point based on which the PA cannot be optimized anymore. To overcome this critical issue, the gradient method can be adopted to "slowly" update the variable $y_{n,j,s}$'s as in [38]. Once, $y_{n,j,s}$'s are changed slowly, the PA can be optimized more carefully. Hence, a better solution can be achieved [38]. In particular, the gradient of $y_{n,j,s}$ as in the objective function of problem (3.21) can be given as $R_{n,j,s}$. Then, the gradient projection method can be described as follows:

$$\vec{Y}^{k+1} = P_{\Omega}(\vec{Y}^k + \lambda^k \vec{R}), \tag{3.22}$$

where $\vec{Y}^k$ and $\vec{Y}^{k+1}$ are the value of $\vec{Y}$ at step k and $k+1$, respectively, $\vec{R}$ represents the vector generated from $R_{n,j,s}$'s, λ_k is a small diminishing gradient step size, and $P_\Omega(\cdot)$ denotes the projection which is further described as the following quadratic problem.

$$\min_{\vec{Y}} \quad ||\vec{Y} - \vec{\hat{Y}}||_2^2 \tag{3.23a}$$

$$\text{s.t.} \quad \text{constraints (3.21b) and (3.21c)},$$

$$0 \leq y_{n,j,s} \leq 1, \ \forall (n,j) \in \mathcal{N}, \ \forall s \in \mathcal{S}, \tag{3.23b}$$

where $\vec{\hat{Y}}$ is the vector generated from all the variables $\hat{y}_{n,j,s} = y^k_{n,j,s} + \lambda^k R_{n,j,s}$. The above updating process can guarantee to converge to the local optimal value of $y_{n,j,s}$'s if the λ_k is chosen carefully so that $\lambda_k \to 0$ when $k \to \infty$ [38].

On the other hand, the step of updating $y_{n,j,s}$ is equivalent to solve

$$\min_{\vec{Y}} \quad - \sum_{\forall (n,j) \in \mathcal{N}} \sum_{s \in \mathcal{S}} R_{n,j,s} y_{n,j,s} + \frac{1}{2c} \sum_{\forall (n,j) \in \mathcal{N}} \sum_{s \in \mathcal{S}} (y_{n,j,s} - \hat{y}_{n,j,s})^2 \tag{3.24a}$$

$$\text{s.t.} \quad \text{constraints (3.21b) and (3.21c)},$$

$$0 \leq y_{n,j,s} \leq 1, \ \forall (n,j) \in \mathcal{N}, \ \forall s \in \mathcal{S}. \tag{3.24b}$$

The problem (3.24) can be solved by the proximal minimization algorithm which must converge to a stationary solution of the problem (3.21) as shown in [38].

3.3 PA with Given SA

In this section, we study the PA problem and describe the successive convex approximation (SCALE) algorithm in [27] to solve it.

3.3.1 PA Problem with Greedy and Matching SA

In order for the PA problem to be applied to a more general case when there are more than one source of interference, we will transform the objective function (3.7) by using (3.8) and (3.9). Thus, the interference becomes

$$I''^{\mathsf{U}}_{n,s}\left(\vec{X},\vec{P}\right) = \sum_{j\in\mathcal{N}/n} x^{\mathsf{U}}_{j,s}G^{\mathsf{U}}_{j,s}p^{\mathsf{U}}_{j,s} + \sum_{j'\in\mathcal{N}} x^{\mathsf{D}}_{j',s}\epsilon(p^{\mathsf{D}}_{j',s})^{\theta}, \tag{3.25}$$

$$\begin{aligned} I''^{\mathsf{D}}_{n,s}\left(\vec{X},\vec{P}\right) = &\sum_{j\in\mathcal{N}/n} (x^{\mathsf{D}}_{j,s}G^{\mathsf{D}}_{j,s}p^{\mathsf{D}}_{j,s} + x^{\mathsf{U}}_{j,s}G_{j,n,s}p^{\mathsf{U}}_{j,s}) \\ &+ x^{\mathsf{U}}_{n,s}\epsilon(p^{\mathsf{U}}_{n,s})^{\theta}. \end{aligned} \tag{3.26}$$

The objective function with general interference is reformulated as

$$\max_{\vec{X},\vec{P}} R_{\mathsf{G}} = \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} \log\left(1 + \frac{x^{\mathsf{D}}_{n,s}G^{\mathsf{D}}_{n,s}p^{\mathsf{D}}_{n,s}}{I''^{\mathsf{D}}_{n,s}\left(\vec{X},\vec{P}\right) + N_0}\right) \tag{3.27}$$

$$+ \log\left(1 + \frac{x^{\mathsf{U}}_{n,s}G^{\mathsf{U}}_{n,s}p^{\mathsf{U}}_{n,s}}{I''^{\mathsf{U}}_{n,s}\left(\vec{X},\vec{P}\right) + N_0}\right)$$

$$\text{s.t.} \sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}} p^{\mathsf{D}}_{n,s} \le P_{\mathsf{BS}}, \tag{3.28}$$

$$\sum_{s\in\mathcal{S}} p^{\mathsf{U}}_{n,s} \le P_n,\ \forall n \in \mathcal{N}. \tag{3.29}$$

When the SA is given, this optimization problem is non-convex which is difficult to calculate the optimal solution. Therefore, we will apply the SCALE method to solve it.

From [27], we have the lower bound for any $z \ge 0$ and $\bar{z} \ge 0$ as

$$\log(1+z) \ge \alpha_{\bar{z}} \log z + \beta_{\bar{z}}, \tag{3.30}$$

that is tight at $z = \bar{z}$, where

$$\alpha_{\bar{z}} = \frac{\bar{z}}{1+\bar{z}}, \beta_{\bar{z}} = \log(1+\bar{z}) - \frac{\bar{z}}{1+\bar{z}}\log \bar{z}. \tag{3.31}$$

We use the convention that $\log(0) = -\infty$ and $0\log(0) = 0$.

Applying (3.30) to our objective function, we obtain

$$R_{\mathsf{G}}(\vec{X},\vec{P}) \geq \tilde{R}_{\mathsf{G}}(\vec{X},\vec{P},\alpha,\beta) = \tag{3.32}$$

$$\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[\alpha^{\mathsf{D}}_{n,s}\log\left(\frac{x^{\mathsf{D}}_{n,s}G^{\mathsf{D}}_{n,s}p^{\mathsf{D}}_{n,s}}{I''^{\mathsf{D}}_{n,s}\left(\vec{X},\vec{P}\right)+N_0}\right)+\beta^{\mathsf{D}}_{n,s}\right.$$

$$\left.+\alpha^{\mathsf{U}}_{n,s}\log\left(\frac{x^{\mathsf{U}}_{n,s}G^{\mathsf{U}}_{n,s}p^{\mathsf{U}}_{n,s}}{I''^{\mathsf{U}}_{n,s}\left(\vec{X},\vec{P}\right)+N_0}\right)+\beta^{\mathsf{U}}_{n,s}\right].$$

It can be noted that the bound is tight at

$$\bar{z}^{\mathsf{D}}_{n,s}=\frac{x^{\mathsf{D}}_{n,s}G^{\mathsf{D}}_{n,s}p^{\mathsf{D}}_{n,s}}{I''^{\mathsf{D}}_{n,s}\left(\vec{X},\vec{P}\right)+N_0}, \tag{3.33}$$

$$\bar{z}^{\mathsf{U}}_{n,s}=\frac{x^{\mathsf{U}}_{n,s}G^{\mathsf{U}}_{n,s}p^{\mathsf{U}}_{n,s}}{I''^{\mathsf{U}}_{n,s}\left(\vec{X},\vec{P}\right)+N_0}. \tag{3.34}$$

By using transformation $\vec{\tilde{P}}=\log\vec{P}$, we have

$$\tilde{R}_{\mathsf{G}}(\vec{X},\vec{\tilde{P}},\alpha,\beta)=\sum_{n\in\mathcal{N}}\sum_{s\in\mathcal{S}}\left[\alpha^{\mathsf{D}}_{n,s}\log\left(G^{\mathsf{D}}_{n,s}\right)+\beta^{\mathsf{D}}_{n,s}+\alpha^{\mathsf{D}}_{n,s}\tilde{p}^{\mathsf{D}}_{n,s}\right. \tag{3.35}$$

$$-\alpha^{\mathsf{D}}_{n,s}\log\left(\sum_{j\in\mathcal{N}/n}\left(x^{\mathsf{D}}_{j,s}G^{\mathsf{D}}_{j,s}e^{\tilde{p}^{\mathsf{D}}_{n,s}}+x^{\mathsf{U}}_{j,s}G_{j,n,s}e^{\tilde{p}^{\mathsf{U}}_{n,s}}\right)\right.$$

$$\left.+x^{\mathsf{U}}_{n,s}\epsilon e^{\tilde{p}^{\mathsf{U}}_{n,s}\theta}+N_0\right)+\alpha^{\mathsf{U}}_{n,s}\log\left(G^{\mathsf{U}}_{n,s}\right)+\beta^{\mathsf{U}}_{n,s}$$

$$+\alpha^{\mathsf{U}}_{n,s}\tilde{p}^{\mathsf{U}}_{n,s}-\alpha^{\mathsf{U}}_{n,s}\log\left(\sum_{j\in\mathcal{N}/n}x^{\mathsf{U}}_{j,s}G^{\mathsf{U}}_{j,s}e^{\tilde{p}^{\mathsf{U}}_{j,s}}\right.$$

$$\left.\left.+\sum_{j'\in\mathcal{N}}x^{\mathsf{D}}_{j',s}\epsilon e^{\tilde{p}^{\mathsf{D}}_{j',s}\theta}+N_0\right)\right].$$

Algorithm 2 SCALE-BASED PA ALGORITHM FOR GREEDY/MATCHING BASED SA

1: Start: any value of $p^{\mathsf{D}}_{n,s}$'s and $q^{\mathsf{U}}_{n,s}$'s satisfying (3.28), (3.29).
2: **repeat**
3: Calculate $\bar{z}^{\mathsf{U}}_{n,s}$ and $\bar{z}^{\mathsf{D}}_{n,s}$ as in (3.33) and (3.34).
4: Use $\bar{z}^{\mathsf{U}}_{n,s}$ and $\bar{z}^{\mathsf{D}}_{n,s}$ to update α, β as in (3.31).
5: Solve the problem (3.36) to obtain $\vec{\tilde{Q}}$.
6: Update $\vec{P} = \exp(\vec{\tilde{P}})$.
7: **until** Convergence.
8: Return $\vec{P}$

$\tilde{R_{\mathsf{G}}}(\vec{X}, \vec{P}, \alpha, \beta)$ is now a concave function of $\vec{\tilde{P}}$ as in ([37], Lemma 1). Then, for given α, β and $\vec{X}$, the problem (3.27) can be described as follows:

$$\max_{\vec{\tilde{P}}} \ \tilde{R_{\mathsf{G}}}(\vec{X}, \vec{P}, \alpha, \beta) \tag{3.36}$$

$$\text{s.t.} \ \sum_{s \in \mathcal{S}} e^{\tilde{p}^{\mathsf{D}}_{n,s}} \leq P_{\mathsf{BS}}, \tag{3.37}$$

$$\sum_{s \in \mathcal{S}} x^{\mathsf{U}}_{n,s} e^{\tilde{p}^{\mathsf{U}}_{s}} \leq P_n, \ \forall n \in \mathcal{N}. \tag{3.38}$$

The problem is a standard convex maximization problem that can be solved optimally by any standard methods. After we have found the optimal value of $\vec{\tilde{P}}$, $\vec{P}$ can obtained by using $\vec{P} = \exp(\vec{\tilde{P}})$ where $\exp(\vec{\tilde{P}})$ denotes an element-by-element operation on the vector $\vec{\tilde{P}}$. The algorithm aims to optimize the lower bound of $\tilde{R_{\mathsf{G}}}(\vec{X}, \vec{\tilde{P}}, \alpha, \beta)$. Therefore, we need to tighten the bound successively by using the new power transmission solution to update the choice of α, β. The process of iteratively updating $\bar{z}^{\mathsf{U}}_{s}$'s, $\bar{z}^{\mathsf{D}}_{s}$'s as well as α, β, is the SCALE-based PA algorithm to maximize DL and UL sum-rate, which is summarized in Algorithm 2. The the algorithm is guaranteed to converge as shown in the following Proposition.

Proposition 1. *The Algorithm 2 converges after a finite number of iterations.*

Proof. The process of iteratively updating $\bar{z}^{\mathsf{U}}_{s}$'s, $\bar{z}^{\mathsf{D}}_{s}$'s, and α, β as in (3.33), (3.34), and (3.31) will always guarantee that the optimal solution of problem (3.36) in the previous iteration is a feasible point in the feasible set of that problem in the next iteration. Thus, the algorithm is guaranteed to converge due to the monotonic increase of the objective function in problem (3.36) after each iteration. Hence, Algorithm 2 converges after a finite number of iterations. □

3.3.2 PA Problem with for Gradient Updated SA

3.3.2.1 Reformulation

In this section, we first reformulate the problem (3.7) into a sum-rate maximization problem when $x^{\mathsf{U}}_{n,s}$'s $x^{\mathsf{U}}_{n,s}$'s are known. Then a numerical method is investigated to solve this problem. For simplicity, we use new power variables representing the transmission power for all users on each SC. In particular, let us denote q^{U}_s and q^{D}_s as the transmission power over SC s on the UL side and DL side, respectively. The relation between these power variables and the power of BS and users on SCs can be given as

$$q^{\mathsf{U}}_s = \sum_{n\in\mathcal{N}} x^{\mathsf{U}}_{n,s} p^{\mathsf{U}}_{n,s}, \quad q^{\mathsf{D}}_s = \sum_{n\in\mathcal{N}} x^{\mathsf{D}}_{n,s} p^{\mathsf{D}}_{n,s}. \tag{3.39}$$

Then, the self-interference over SC s on UL transmission can be rewritten as $I'^{\mathsf{U}}_s\left(q^{\mathsf{D}}_s\right) = \epsilon\left(q^{\mathsf{D}}_s\right)^{\theta}$. Based on this result, the rate for UL transmission over SC s can be calculated as

$$R'^{\mathsf{U}}_s\left(\vec{X}, q^{\mathsf{D}}_s, q^{\mathsf{U}}_s\right) = \log\left(1 + \frac{q^{\mathsf{U}}_s G^{\mathsf{U}}_s(\vec{X})}{\epsilon\left(q^{\mathsf{D}}_s\right)^{\theta} + N_0}\right), \tag{3.40}$$

where $G^{\mathsf{U}}_s(\vec{X}) = \sum\limits_{n\in\mathcal{N}} x^{\mathsf{U}}_{n,s} G^{\mathsf{U}}_{n,s}$. On the DL side, the interference over SC s can be given as

$$I'^{\mathsf{D}}_s\left(\vec{X}, q^{\mathsf{U}}_s\right) = q^{\mathsf{U}}_s G^{\mathsf{C}}_s(\vec{X}) + \epsilon^{\mathsf{U}}_s(\vec{X})\left(q^{\mathsf{U}}_s\right)^{\theta},$$

where $G^{\mathsf{C}}_s(\vec{X}) = \sum\limits_{n\in\mathcal{N}} \sum\limits_{j\in\mathcal{N}/n} x^{\mathsf{D}}_{n,s} x^{\mathsf{U}}_{j,s} G_{j,n,s}$ and $\epsilon^{\mathsf{U}}_s(\vec{X}) = \epsilon \sum\limits_{n\in\mathcal{N}} x^{\mathsf{D}}_{n,s} x^{\mathsf{U}}_{n,s}$. Then, the rate for DL transmission over SC s can be calculated as

$$R'^{\mathsf{D}}_s\left(\vec{X}, q^{\mathsf{D}}_s, q^{\mathsf{U}}_s\right) = \log\left(1 + \frac{q^{\mathsf{D}}_s G^{\mathsf{D}}_s(\vec{X})}{I'^{\mathsf{D}}_s\left(\vec{X}, q^{\mathsf{U}}_s\right) + N_0}\right), \tag{3.41}$$

where $G_s^{\mathsf{D}}(\vec{X}) = \sum_{n\in\mathcal{N}} x_{n,s}^{\mathsf{D}} G_{n,s}^{\mathsf{D}}$. Let $\vec{Q} \triangleq \left\{q_s^{\mathsf{U}}, q_s^{\mathsf{D}}\right\}_{s\in\mathcal{S}}$. Then, the problem (3.7) is equivalent to the sum-rate maximization problem when the SA is given

$$\begin{aligned} \max_{\vec{Q}} \;\; R_{\vec{X}}(\vec{Q}) = \sum_{s\in\mathcal{S}} \Bigg[&\log\left(1 + \frac{G_s^{\mathsf{U}}(\vec{X}) q_s^{\mathsf{U}}}{\epsilon\left(q_s^{\mathsf{D}}\right)^{\theta} + N_0}\right) \\ &+ \log\left(1 + \frac{G_s^{\mathsf{D}}(\vec{X}) q_s^{\mathsf{D}}}{G_s^{\mathsf{C}}(\vec{X}) q_s^{\mathsf{U}} + \epsilon_s^{\mathsf{U}}(\vec{X})\left(q_s^{\mathsf{U}}\right)^{\theta} + N_0}\right)\Bigg] \end{aligned} \tag{3.42a}$$

$$\text{s.t.} \;\; \sum_{s\in\mathcal{S}} q_s^{\mathsf{D}} \leq P_{\mathsf{BS}}, \tag{3.42b}$$

$$\sum_{s\in\mathcal{S}} x_{n,s}^{\mathsf{U}} q_s^{\mathsf{U}} \leq P_n, \; \forall n \in \mathcal{N}. \tag{3.42c}$$

In the above optimization problem, the objective function is non-convex. Hence, it is very difficult to find the optimal solution of this problem. In the next section, we leverage the SCALE algorithm in [27] to solve (3.42).

3.3.2.2 SCALE-Based Algorithm for Gradient Updated SA

In this section, we again apply the SCALE algorithm [27] to find the PA for each user on each transmission side and each SC when the SA is assumed given. The idea of this numerical method is to relax the non-convex objective function to its lower bound which is convex with respect to q_s^{U}'s and q_s^{D}'s in order to obtain a relaxed convex problem. This convex problem is then solved optimally. Then, the lower bound is updated iteratively to tighten the non-convex objective function at the optimal point.

We use the convention that $\log(0) = -\infty$ and $0\log(0) = 0$. By using (3.30), we have

$$\begin{aligned} R_{\vec{X}}(\vec{Q}) \geq \bar{R}_{\vec{X}}(\vec{Q}, \alpha, \beta) \triangleq \sum_{s=1}^{S} \Bigg[&\alpha_s^{\mathsf{U}} \log\left(\frac{G_s^{\mathsf{U}}(\vec{X}) q_s^{\mathsf{U}}}{\epsilon\left(q_s^{\mathsf{D}}\right)^{\theta} + N_0}\right) + \beta_s^{\mathsf{U}} \\ + \alpha_s^{\mathsf{D}} \log\left(\frac{G_s^{\mathsf{D}}(\vec{X}) q_s^{\mathsf{D}}}{G_s^{\mathsf{C}}(\vec{X}) q_s^{\mathsf{U}} + \epsilon_s^{\mathsf{U}}(\vec{X})\left(q_s^{\mathsf{U}}\right)^{\theta} + N_0}\right) &+ \beta_s^{\mathsf{D}} \Bigg]. \end{aligned} \tag{3.43}$$

We denote $\alpha \triangleq \left\{\alpha_s^{\mathsf{U}}, \alpha_s^{\mathsf{D}}\right\}$ and $\beta \triangleq \left\{\beta_s^{\mathsf{U}}, \beta_s^{\mathsf{D}}\right\}$. The terms α_s^{U} and β_s^{U} are corresponding to the relaxation of UL and DL part in R_s^{U}. Similarly, the terms α_s^{D} and β_s^{D} are corresponding to

Algorithm 3 SCALE-BASED ALGORITHM FOR GRADIENT UPDATED SA

1: Start: any value of q_s^{D}'s and q_s^{U}'s satisfying (3.42b), (3.42c).
2: **repeat**
3: Calculate $\bar{z}_s^{\mathsf{U}}$ and $\bar{z}_s^{\mathsf{D}}$ as in (3.44) and (3.45).
4: Use $\bar{z}_s^{\mathsf{U}}$ and $\bar{z}_s^{\mathsf{D}}$ to update α, β as in (3.31).
5: Solve the problem (3.47) to obtain $\vec{\tilde{Q}}$.
6: Update $\vec{Q} = \exp(\vec{\tilde{Q}})$.
7: **until** Convergence.
8: Return $\vec{P}$ from $\vec{Q}$ as $p_{n,s}^{\mathsf{U}} = x_{n,s}^{\mathsf{U}} q_s^{\mathsf{U}}, p_{n,s}^{\mathsf{D}} = x_{n,s}^{\mathsf{D}} q_s^{\mathsf{D}}$.

the relaxation of UL and DL part in R_s^{D}. It can be noted that the bound (3.43) is tight at

$$\bar{z}_s^{\mathsf{U}} = \Gamma_{s,\vec{X}}^{\mathsf{U}}(\vec{Q}) = \frac{G_s^{\mathsf{U}}(\vec{X}) q_s^{\mathsf{U}}}{\epsilon \left(q_s^{\mathsf{D}}\right)^{\theta} + N_0}, \tag{3.44}$$

$$\bar{z}_s^{\mathsf{D}} = \Gamma_{s,\vec{X}}^{\mathsf{D}}(\vec{Q}) = \frac{G_s^{\mathsf{D}}(\vec{X}) q_s^{\mathsf{D}}}{G_s^{\mathsf{C}}(\vec{X}) q_s^{\mathsf{U}} + \epsilon_s^{\mathsf{U}}(\vec{X}) \left(q_s^{\mathsf{U}}\right)^{\theta} + N_0}. \tag{3.45}$$

By using transformation $\vec{\tilde{Q}} = \log \vec{Q}$, we obtain

$$\begin{aligned} \bar{R}_{\vec{X}}(\vec{\tilde{Q}}, \alpha, \beta) = \sum_{s=1}^{S} \Big[& \alpha_s^{\mathsf{U}} \tilde{q}_s^{\mathsf{U}} + \eta_s^{\mathsf{U}} - \alpha_s^{\mathsf{U}} \log\left(\epsilon e^{\theta \tilde{q}_s^{\mathsf{D}}} + N_0\right) \\ & + \alpha_s^{\mathsf{D}} \tilde{q}_s^{\mathsf{D}} + \eta_s^{\mathsf{D}} - \alpha_s^{\mathsf{D}} \log\left(G_s^{\mathsf{C}}(\vec{X}) e^{\tilde{q}_s^{\mathsf{D}}} + \epsilon_s^{\mathsf{U}}(\vec{X}) e^{\theta \tilde{q}_s^{\mathsf{U}}} + N_0\right)\Big] \end{aligned} \tag{3.46}$$

where $\eta_s^{\mathsf{U}} = \alpha_s^{\mathsf{U}} \log G_s^{\mathsf{U}}(\vec{X}) + \beta_s^{\mathsf{U}}$ and $\eta_s^{\mathsf{D}} = \alpha_s^{\mathsf{D}} \log G_s^{\mathsf{D}}(\vec{X}) + \beta_s^{\mathsf{D}}$. As can be observed, $\bar{R}_{\vec{X}}(\vec{\tilde{Q}}, \alpha, \beta)$ is a concave function of $\vec{\tilde{Q}}$. Then, for given α, β, the relaxation of problem (3.42) can be described as follows:

$$\max_{\vec{\tilde{Q}}} \; \bar{R}_{\vec{X}}(\vec{\tilde{Q}}, \alpha, \beta) \tag{3.47a}$$

$$\text{s.t.} \; \sum_{s \in \mathcal{S}} e^{\tilde{q}_s^{\mathsf{D}}} \leq P_{\mathsf{BS}}, \tag{3.47b}$$

$$\sum_{s \in \mathcal{S}} x_{n,s}^{\mathsf{U}} e^{\tilde{q}_s^{\mathsf{U}}} \leq P_n, \; \forall n \in \mathcal{N}, \tag{3.47c}$$

We now have a standard convex maximization problem that is efficiently solved in the dual domain. Once a solution is obtained, we may transform back to Q-space with $\vec{Q} = \exp(\vec{\tilde{Q}})$.

Here we are optimizing the lower bound of $R_{\vec{X}}(\vec{Q})$. As a result, it is natural to tighten the bound successively by updating the choice of $\alpha,\ \beta$ according to the new power transmission solution. Then, by iteratively updating $\bar{z}_s^{\mathsf{U}}$'s, $\bar{z}_s^{\mathsf{D}}$'s as well as $\alpha,\ \beta$, we obtain the SCALE-Based algorithm to maximize DL and UL sum-rate, as summarized in Algorithm 3. The convergence of the algorithm is guaranteed due to the following Proposition.

Proposition 2. *The Algorithm 3 converges after a finite number of iterations.*

Proof. By iteratively updating $\bar{z}_s^{\mathsf{U}}$'s, $\bar{z}_s^{\mathsf{D}}$'s, and $\alpha,\ \beta$ as in (3.33), (3.34), and (3.31), we always have the fact that the optimal solution of problem (3.36) in the previous iteration is a feasible point in the feasible set of that problem in the next iteration. Hence, the convergence of the algorithm is guaranteed due to the monotonic increase of the objective function in problem (3.36) after each iteration. Hence, the Algorithm 2 will converge after a finite number of iterations. □

3.4 Resource Allocation Algorithms

In this section, we will present the algorithms that will be used in the simulation.

3.4.1 Proposed FD Matching Based Algorithm

In our proposed FD matching based algorithm, the SA problem is solved by using the matching method and the PA problem is solved by the SCALE-based algorithm. In order to compute the weights for the matching matrix, a fast greedy allocation will be employed to find an initial SA solution and then the initial PA solution for calculating the weights can be found by applying the SCALE method. The detail of the proposed algorithm is shown in Algorithm 4.

Algorithm 4 FD Matching Based Algorithm

1: Run Algorithm 1 to get $\vec{X}$.
2: Run Algorithm 2 to get $\vec{P}$.
3: Use $\vec{P}$, (3.12), (3.13), and (3.14) to calculate the weights in the matching matrix M.
4: Solve M for $\vec{X}$.
5: Run Algorithm 2 to get $\vec{P}$.
6: Calculate sum-rate from (3.7) using $\vec{P}$ and $\vec{X}$.

3.4.2 Proposed FD Gradient Algorithm

In our second proposed FD algorithm, firstly, the SA variables are relaxed from integer values into real values and then in each iteration, they are slowly updated by a gradient method. Then with the updated SA variables, the PA problem is solved by the SCALE method. method. The detail of the proposed algorithm is demonstrated in Algorithm 5.

Algorithm 5 FD Gradient Algorithm

1: Start: $q_s^{\mathsf{D}} = P_{\mathsf{BS}}/S$, $q_s^{\mathsf{U}} = \min_{n\in\mathcal{N}} P_n/S \ \forall s \in \mathcal{S}$.
2: **repeat**
3: Fix $\vec{Q}$, then update $\vec{X}$ using (3.22).
4: Update $G_s^{\mathsf{U}}(\vec{X}), G_s^{\mathsf{D}}(\vec{X}), \epsilon_s^{\mathsf{U}}(\vec{X}), G_s^{\mathsf{C}}(\vec{X})$.
5: Fix $\vec{X}$, solve $\vec{Q}$ by applying Algorithm 3.
6: **until** Convergence.
7: Return $\vec{X}$ from $\vec{Y}$ as $x_{n,s}^{\mathsf{D}} = \sum_{j\in\mathcal{N}} y_{n,j,s}, x_{j,s}^{\mathsf{U}} = \sum_{n\in\mathcal{N}} y_{n,j,s}$.

Proposition 3. *The iterative procedure presented in Algorithm 5 converges after a finite number of iterations.*

Proof. Through Proposition 2, the objective function of problem (3.47) increases after each iteration. Hence, the sum-rate will be improved by Algorithm 3. In addition, the gradient update of $y_{n,j,s}$'s further improves this sum-rate value. Therefore, Algorithm 5 will monotonically increase the objective function of problem (3.7), which leads to the convergence. □

3.4.3 FD Greedy Algorithm

This simple algorithm is considered as the input step for finding the initial weights in our proposed FD matching based algorithm. Algorithm 1 is used to find the SA solution, then we compute the PA solution by using Algorithm 2.

3.4.4 HD Greedy Algorithm

In this algorithm, each SC is assigned at most one link, either UL or DL transmission. This algorithm is similar to Algorithm 1 where the uniform power distribution is employed for this method as well. For SC allocation, each SC is assigned for the user with its DL or UL transmission with the highest achievable rate instead of a pair of UL and DL transmissions as in the FD algorithms.

Table 3.1: Simulation System Parameters

Parameters	Value
WINNER-II Model's parameters	A = 36.8, B = 43.8, C = 23, and $f_c = 2.5GHz$
Minimum distance	50m
Maximum distance	100m
Number of nodes	10
Number of carriers	20
Power of base station	4W
Power of node	0.4W
Noise power N_0	10^-12W
ϵ	10^-12
θ	0.5

3.5 Simulation Results

We consider a single cell network in which the users are placed randomly. The channel gains are generated by considering both Rayleigh fading and path loss which is modeled based on the WINNER-II Model as $PL(d) = A\log_{10}(d) + B + C\log_{10}(f_c/5)$, where d is the distance between two terminals. The detail of the parameters used in our simulation is shown in Table 3.1. In Figs. 3.6, the maximum powers of the BS and nodes are multiplied with a scaling factor Ω to analyze the effect of the power on the system's sum-rate.

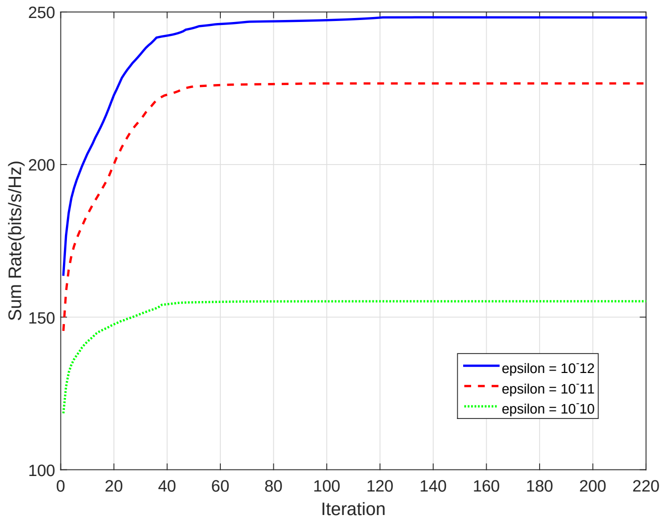

Figure 3.4: Total rate versus the iteration index.

First, we examine the convergence of our proposed gradient algorithm by showing the variations of system sum-rate corresponding to different values of ϵ over iterations by using the combination of Algorithm 3 and Algorithm 5 ("Proposed Alg.") in Fig. 3.4. To obtain these simulation results, we set $\theta = 1$. It can be observed that our proposed algorithm converge for both inner and outer loops. As the value of θ decreases, the number of iterations needed for convergence increases. This is because there is more SI with large value of θ, thus the number of choices for allocation is smaller.

In Figs. 3.5–3.8, we show the variations of the sum-rate achieved by our proposed matching based and gradient based algorithm along with two greedy algorithms presented in the previous section over the changes of some network parameters, such as the interference factor ϵ in Fig. 3.5, the maximum transmission power in Fig. 3.6, the number of SCs in Fig. 3.7, and the number of nodes in Fig. 3.8. As it can been seen from these figures, the proposed FD matching based and gradient based algorithm surpasses the two greedy algorithms in all studied scenarios. It can also be noted that the gradient algorithm achieve a much better result than the matching algorithm. However, the gradient method takes around 100 iteration to reach the final solution whereas the matching algorithm will only take one. Additionally, we can also see that all of the FD algorithms achieved much better sum-rate than the HD one.

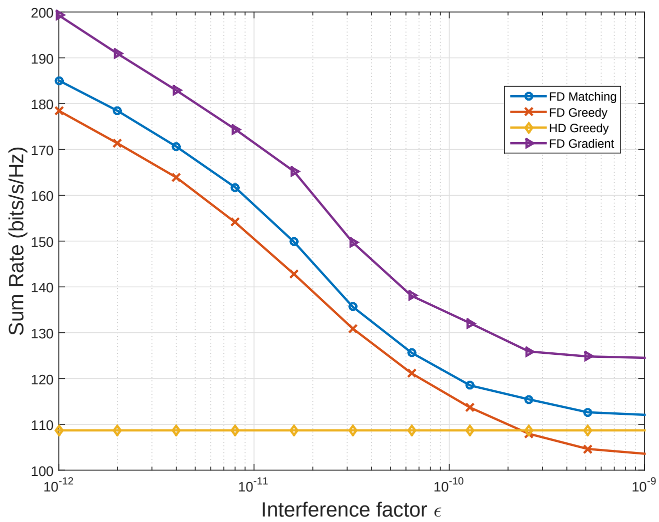

Figure 3.5: Total rate versus the interference factor ϵ.

As can be seen in Fig. 3.5, the higher value of interference factor ϵ results in the lower sum-rate in our system when it is in FD mode. This can be easily explained since the higher value of ϵ means that the SI cancellation is less effective in preventing the interference. Thus it results in lowering the advantages of FD techniques. Moreover,it can be observed that when ϵ is greater than 10^{-10}, the performance of FD greedy algorithm starts to become worse than the HD one while the sum-rate of both of the proposed algorithms are still higher than the HD.

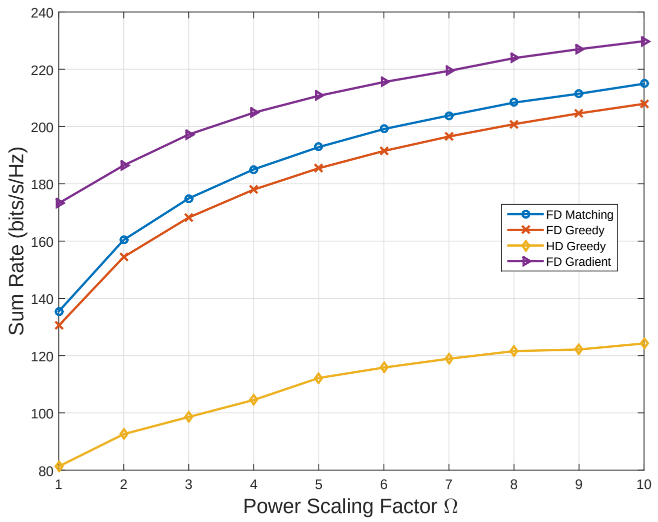

Figure 3.6: Sum-rate versus the power scaling factor Ω.

In Fig. 3.6, increasing the transmission powers of BS and nodes via increasing scaling factor Ω also yields a higher sum-rate achieved by the network as expected. It can be noticed that for low power values, the gap between the gradient algorithm and the rest is quite big. As the power increases, the gap is getting smaller as well.

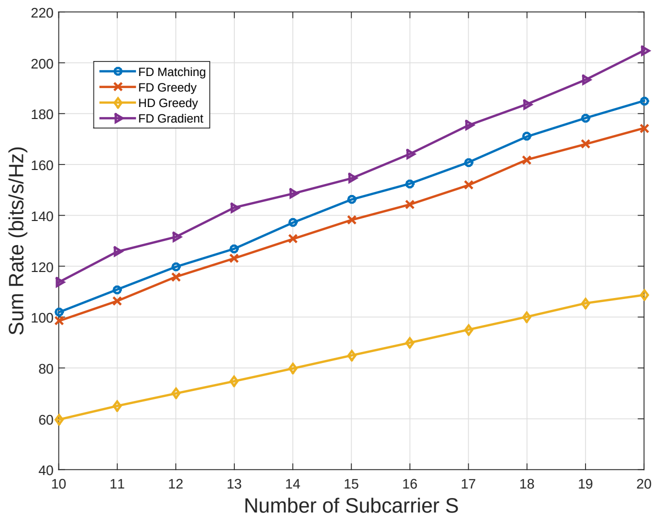

Figure 3.7: Sum-rate versus the number of subcarriers.

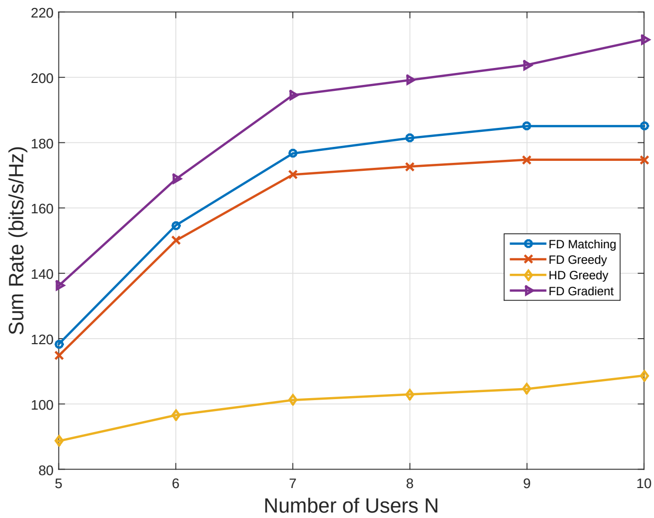

Figure 3.8: Sum-rate versus the number of users.

Fig. 3.7 and Fig. 3.8 also show that the higher number of SCs or higher number of nodes also lead to the higher network sum-rate. This is because with more users or subcarriers, there are more better options for resource allocation within the networks, thus the system sum-rate can be improved. Moreover, it can also be seen from the results in Fig. 3.5 to Fig. 3.8 that the sum-rate due to the proposed FD matching based algorithm is about 5 % higher than that of the FD greedy algorithm and almost two times better than the sum-rate of the HD greedy algorithm. Overall, the gradient algorithm achieves the best result in comparison with the rest algorithms. The performance of the matching method is not as good because the weight of the matching matrix cannot reflect every possible cases that can happen in our model.

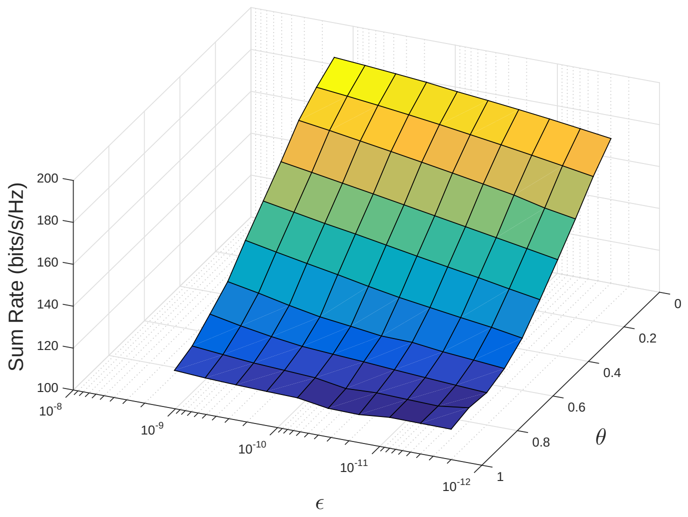

Figure 3.9: Sum-rate versus theta versus epsilon.

Fig. 3.9 demonstrates the influences of the SI cancellation parameters ϵ and θ on the sum-rate of our proposed algorithm. It can be seen that the smaller value of θ results in the smaller sum-rate. This is because the power value is less than 1, so with a value of $0 \leq \theta \leq 1$, p^θ is bigger than the original power p. Moreover, the change in θ results in sharper change in the system sum-rate than the change in ϵ, this is because θ is a power parameter while ϵ can only have a linear effect on the interference.

3.6 Summary

In this chapter, we have proposed the FD matching based algorithm and FD gradient base algorithm for joint PA and SA design in FD single cell network with the goal to maximize the system's sum-rate subject to constraints on the power transmission limit. In the former approach, the SA is solved using the bipartite matching method and the PA's solution is found by the SCALE-based. As for the latter method, the integer allocation variables are relaxed into real number, then they are updated with their gradient values. Next, we apply the SCALE method to solve for the PA at the end of each iteration. The process is repeated until the system sum-rate converges. Numerical results have illustrated the efficiency of our proposed algorithms and the influences of different parameters on the performance of our methods.

Chapter 4

Conclusion and Future Work

4.1 Conclusion Remarks

In this thesis, we study the resource allocation problem for a full-duplex (FD) multiuser wireless system consisting of one FD base-station (BS) and multiple FD mobile nodes. Our main focus is to jointly optimize the power allocation (PA) and subcarrier assignment (SA) for both uplink (UL) and downlink (DL) transmissions of all users to maximize the system sum-rate. Our design captures the self-interference of FD transceivers and allows the utilization of each subcarrier for multiple concurrent UP and DL transmissions with the flexibility of mode switching. Since the joint optimization problem is a nonconvex mixed integer program, which is difficult to tackle, we propose to employ the bipartite matching method to address the SA. Toward this end, a fast greedy allocation algorithm is developed to perform initial assignment of UL/DL links to each subcarrier that offers the best sum-rate. Then from the obtained SA solution, we adopt the successive convex approximation approach to solve the PA problem whose results are used to calculate the SA weights for re-optimizing the SA by using the bipartite matching method. Another approach to our problem is to employ an iterative algorithm in which the SA is updated by a gradient method and then solve the PA by the SCALE technique. We then present the numerical results to demonstrate the improvement of our proposed algorithms in comparison with the greedy FD and half-duplex (HD) resource allocation algorithms. Overall, the gradient algorithm achieves the best results which is almost two times better than the HD method. The sum-rate of the bipartite matching approach is about ten percent less than the gradient approach on average. However, it still has better output than the greedy allocation for both FD and HD mode.

4.2 Future Research and Extensions

FD communication is a very promising technology, and there are many potential future research directions in this area, such as the examples below.

- The scheduling in multi-cell environments is an interesting problem for future research direction. Since cell-edge nodes which cause inter-cell interference to neighboring cells, combined with full-duplex networks, can give severe inter-cell interference to each other. In order to solve this problem, a network-wide scheduling and the fractional power control method can be employed to suppress the effect of inter-cell interference on the system performance.
- OFDMA relaying systems has been receiving considerable interest thanks to its coverage expansion ability as well as the reduction in power consumption without incurring the high costs of deploying additional BS. The combination of relaying and OFDMA allows the systems to support heterogeneous data rate services along with guarantee the QoS requirements for next-generation wireless communication networks. However, few studies have been made on the topic of efficient resource allocation and scheduling algorithms for FD OFDMA relaying systems.
- MIMO-OFDM is the dominant technology for air interface in next-generation wireless communication networks. With the addition of FD transmission, the potential of this system can become even greater. However, the effect interference will also be more severe, thus good resource allocation plays a key factor in order to achieve the performance for this type of network.
- A new SI model can be studied in order to better reflect the effect of different interference sources on the overall performance of the FD system.

Overall, these problems require novelty approaches in the aspects of both modeling and solution. Thus, more studies are needed in the future to fully grasp the possible advantages and the weaknesses of the underlying designs in order to utilize them effectively.

4.3 List of Publications

1. T.T. Tran, V.N. Ha, L.B. Le and A. Girard, "Dynamic resource allocation for full-duplex OFDMA wireless cellular networks," in *IEEE 84th Vehicular Technology Conference*, Montréal, Canada, Sep. 2016.

2. T.T. Tran, V.N. Ha, L.B. Le and A. Girard, , “Uplink/downlink matching based resource allocation for full-duplex OFDMA wireless cellular networks,” in *IEEE Wireless Communications and Networking Conference,* San Francisco, United States, Mar. 2017.

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