



Joint minimization of power and delay in wireless access networks

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Joint Minimization of Power and Delay in Wireless Access Networks

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To my lovely parents.

Abstract

In wireless access networks, one of the most recent challenges is reducing the power consumption of the network, while preserving the quality of service perceived by the end users. The present thesis provides solutions to this challenging problem considering two objectives, namely, saving power and minimizing the transmission delay. Since these objectives are conflicting, a tradeoff becomes inevitable. Therefore, we formulate a multi-objective optimization problem with aims of minimizing the network power consumption and transmission delay. Power saving is achieved by adjusting the operation mode of the network Base Stations (BS) from high transmit power levels to low transmit levels or even sleep mode. Minimizing the transmission delay is achieved by selecting the best user association with the network BSs. After exploring typical multi-objective approaches, we resort to the weighted sum method, which enables us to efficiently tune the impact of the power and delay objectives. We cover two different wireless networks, namely IEEE 802.11 Wireless Local Area Networks (WLANs) and cellular networks with Long Term Evolution (LTE).

The first part of this thesis addresses the joint Power-Delay minimization in WLANs. We consider the power consumption of an IEEE 802.11 WLAN, with access points working in infrastructure mode. We provide a realistic delay model used in WLANs, which is a unique feature of our work. Starting from a binary non-linear formulation of the problem, we formulate the Power-Delay minimization problem as a Mixed Integer Linear Programming problem. We study various preference settings that enable to assess the tradeoff between power and delay minimization. We compare our approach with the most frequently deployed WLANs where BSs transmit at a fixed transmit power level while users are associated with the BS delivering the highest signal to noise ratio. The results show that for a power minimization, we obtain power savings of up to 16% whereas for a delay minimization setting, we obtain a delay reduction of up to 6%. An interesting conclusion is driven from our analysis: minimizing the power consumption while minimizing the transmission delay does not lead to maximizing the network energy efficiency.

Due to computational complexity issues, we propose a greedy heuristic algorithm for the Power-Delay minimization problem that yields power savings up to 45% compared with legacy networks.

In the second part of the thesis, we focus on the power-delay tradeoffs in 4G wireless networks. In particular, we cover the LTE technology considering the EARTH model for BS power model and the fair-time sharing model for radio resource allocation. We consider rural and urban deployments, and assess the impact of the end users position in the cell on the achievable tradeoffs. When adequately tuned, our optimization approach reduces the power consumption by 4% and the transmission delay by 8% compared with legacy networks. Moreover, we show that the power savings mainly depend on user distribution and on the power consumption of the sleep mode.

Afterwards, we study the case of a realistic LTE network. The challenging issue, which arises in this case, is the high computational complexity necessary to obtain the optimal solution. Therefore, we propose a Simulated Annealing based heuristic algorithm for the joint Power-Delay minimization problem. We show that the proposed heuristic performs close to the optimal and outperforms existing approaches in terms of cost reduction. Moreover, our heuristic provides power savings of up to 18% and delay reduction of up to 32% in a reasonable time.

Keywords: Green wireless access networks, power consumption, transmission delay, WLANs, IEEE 802.11, broadband wireless networks, LTE, user association, multi-objective optimization, heuristic algorithm.

Résumé

Dans les réseaux d'accès sans-fil, l'un des défis les plus récents est la réduction de la consommation d'énergie du réseau, tout en préservant la qualité de service perçue par les utilisateurs finaux. Cette thèse propose des solutions à ce problème difficile en considérant deux objectifs, l'économie d'énergie et la minimisation du délai de transmission. Comme ces objectifs sont contradictoires, un compromis devient inévitable. Par conséquent, nous formulons un problème d'optimisation multi-objectif dont le but est la minimisation conjointe de la puissance consommée et du délai de transmission dans les réseaux sans-fil. La minimisation de la puissance est réalisée en ajustant le mode de fonctionnement des stations de base (BS) du réseau d'un niveau élevé de puissance d'émission vers un niveau d'émission plus faible ou même en mode veille. La minimisation du délai de transmission est réalisée par le meilleur rattachement des utilisateurs avec les BS du réseau. Après avoir exploré les approches multi-objectives typiques, nous avons recours à la méthode de la somme pondérée, qui nous permet de régler efficacement l'influence des deux objectifs. Nous couvrons deux types de réseaux sans-fil différents, notamment, les réseaux locaux sans-fil (IEEE 802.11 WLAN) et les réseaux cellulaires dotés de la technologie LTE.

La première partie de cette thèse traite la minimisation conjointe de la puissance et du délai dans les réseaux WLAN. Nous considérons la consommation d'énergie du réseau 802.11 WLAN, avec des points d'accès en mode infrastructure. Nous présentons un modèle de délai réaliste utilisé dans les réseaux locaux sans-fil, ce qui est une caractéristique unique de notre travail. A partir d'une formulation non-linéaire binaire du problème, nous transformons le problème de minimisation de la puissance et du délai en un problème de programmation mixte linéaire en nombres entiers. Nous étudions différents paramètres de préférence qui permettent d'évaluer le compromis entre la puissance consommée et le délai de transmission. Nous comparons notre approche avec des approches adoptées dans les réseaux locaux sans-fil les plus déployés où les stations de base transmettent à un niveau de puissance d'émission fixe tandis que les utilisateurs sont associés à la BS délivrant un rapport signal sur bruit le plus élevé. Les résultats montrent que, pour une minimisation de la puissance, on obtient des économies de puissance pouvant aller jusqu'à 16%, alors

que pour un cas de minimisation du délai, on obtient une réduction de délai de l'ordre de 6%. De plus, les résultats de simulations nous mènent à une conclusion très intéressante : la minimisation conjointe de la puissance et du délai n'est pas équivalente à une maximisation de l'efficacité énergétique du réseaux.

En raison de complexité de calcul du problème de minimisation de la puissance et du délai, nous proposons un algorithme heuristique glouton pour ce problème qui donne une réduction de la puissance consommée de l'ordre de 45% par rapport aux réseaux existants.

Dans la deuxième partie de la thèse, nous nous concentrons sur les compromis entre puissance et délai dans les réseaux 4G sans-fil. En particulier, nous couvrons la technologie LTE considérant le modèle du projet EARTH pour celui de la puissance de BS et le modèle de partage des temps équitable (*fair-time sharing*) pour l'allocation des ressources radio. Nous considérons des déploiements ruraux et urbains, et nous avons ainsi évalué l'impact de la position de l'utilisateur final dans la cellule sur les compromis obtenus. Pour un réglage adéquat des poids associés, soit à la puissance consommée, soit au délai de transmission, notre approche d'optimisation réduit la consommation de puissance de 4% et le délai de transmission de 8% par rapport aux réseaux existants. En outre, nous montrons que les économies de puissance dépendent principalement de la distribution des utilisateurs dans le réseau et aussi de la puissance consommée en mode veille.

Ensuite, nous étudions le cas d'un réseau LTE réaliste. La défi majeur, qui se pose dans ce cas, est la haute complexité de calcul nécessaire pour obtenir la solution optimale. Par conséquent, nous proposons une heuristique basée sur la méthode de recuit simulé pour le problème de minimisation conjointe de la puissance et du délai. Nous montrons que l'heuristique proposée offre une solution proche de l'optimal et surpasse les approches existantes en termes de réduction du coût du réseau. De plus, notre heuristique permet une économie de puissance pouvant aller jusqu'à 18% et une réduction de délai pouvant aller jusqu'à 32% pour un temps de calcul raisonnable.

Mots-clés : Réseaux d'accès sans-fil, consommation de puissance, délai de transmission, réseaux locaux sans-fil, IEEE 802.11, réseaux sans-fil à large bande, LTE, rattachement des utilisateurs, optimisation multi-objectifs, algorithme heuristique.

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Résumé Français

0.1 Introduction

Dans les réseaux d'accès sans-fil, l'un des défis les plus récents est la réduction de la consommation d'énergie du réseau, tout en préservant la qualité de service perçue par les utilisateurs finaux. Cette thèse propose des solutions à ce problème difficile en considérant deux objectifs, l'économie d'énergie et la minimisation du délai de transmission. Comme ces objectifs sont contradictoires, un compromis devient inévitable. Par conséquent, nous formulons un problème d'optimisation multi-objectif dont le but est la minimisation conjointe de la puissance consommée et du délai de transmission dans les réseaux sans-fil. La minimisation de la puissance est réalisée en ajustant le mode de fonctionnement des stations de base (BS) du réseau d'un niveau élevé de puissance d'émission vers un niveau d'émission plus faible ou même en mode veille. La minimisation du délai de transmission est réalisée par le meilleur rattachement des utilisateurs avec les BS du réseau. Après avoir exploré les approches multi-objectives typiques, nous avons recours à la méthode de la somme pondérée, qui nous permet de régler efficacement l'influence des deux objectifs. Nous couvrons deux réseaux sans-fil différents en raison de leur pertinence : les réseaux locaux sans-fil (IEEE 802.11 WLAN) et les réseaux cellulaires dotés de la technologie LTE.

0.2 Contributions de la thèse

Le ciblage de l'efficacité énergétique tout en tenant compte des performances du réseau est l'un des plus difficiles problèmes dans les réseaux d'accès sans-fil. Dans cette thèse, nous étudions le problème de la minimisation conjointe de la puissance consommée et du délai de transmission et nous répondons aux questions suivantes :

- Comment optimiser les paramètres conflictuelles de la puissance consommée et du délai dans les réseaux d'accès sans-fil ? Quel est le mode de fonctionnement optimal des BS et quel est le rattachement optimal des utilisateurs qui minimise conjointement la consomma-

tion de la puissance du réseau et du délai de transmission utilisateurs ?

- Résoudre le problème d’optimisation de la puissance et de retard est très difficile à cause du couplage complexe du mode de fonctionnement de BS et du rattachement des utilisateurs. Y a-t-il des algorithmes efficaces qui ont une faible complexité de calcul et qui donnent des solutions quasi-optimales ? Y a-t-il des algorithmes avec des solutions originales qui peuvent être appliquées pour des scénarios réels ?

La première étape pour répondre à ces questions est d’étudier les approches existantes qui ont été considérées dans la littérature pour améliorer l’efficacité énergétique des réseaux d’accès sans-fil. Donc, nous présentons un aperçu sur les activités de recherche pertinentes dans les réseaux “green” sans-fil. Nous classons les dernières activités selon différentes approches qui fonctionnent à différentes échelles de temps. Nous commençons avec les approches de planification et de déploiement. Ensuite, nous présentons des études sur l’approche de dimensionnement de la cellule associée à l’approche de l’association de l’utilisateur. Enfin, nous mettons en avant l’approche de planification. Les contributions de cette thèse consistent à proposer de nouvelles approches qui mettent en oeuvre les points forts des approches existantes pour générer des économies de la puissance, et combler le vide dans la littérature en tenant compte ainsi de la minimisation du délai de transmission.

0.3 Minimisation conjointe de la puissance et du délai dans les réseaux locaux sans-fil (WLANs)

La première partie de cette thèse traite la minimisation conjointe de la puissance et du délai dans les réseaux WLAN. Nous considérons la consommation d’énergie du réseau 802.11 WLAN, avec des points d’accès en mode infrastructure. Nous présentons un modèle de délai réaliste utilisé dans les réseaux locaux sans-fil, ce qui est une caractéristique unique de notre travail. Précisément, nous considérons un système de partage de débit équitable (*fair-rate sharing*) parce qu’il est le modèle de partage des ressources qui en découle du protocole Carrier Sense Multiple Access (CSMA). Cette politique de partage des ressources assure l’équité utilitaire, ce qui signifie que tous les utilisateurs ont le même partage de la capacité globale du système, conduisant à des taux égaux. A partir d’une formulation non-linéaire binaire du problème, nous transformons le problème de minimisation de la puissance et du délai en un problème de programmation mixte linéaire en nombres entiers. Nous étudions différents paramètres de préférence qui permettent d’évaluer le compromis entre la puissance consommée et le délai de transmission. Nous comparons notre approche avec des approches adoptées dans les réseaux locaux sans-fil les plus déployés où les stations de base transmettent à un niveau de puissance d’émission fixe tandis que les utilisateurs sont

raccordés à la BS délivrant un rapport signal sur bruit le plus élevé.

Les résultats montrent que, pour une minimisation de la puissance, on obtient des économies de puissance pouvant aller jusqu'à 16%, alors que pour un cas de minimisation du délai, on obtient une réduction de délai de l'ordre de 6%. De plus, les résultats de simulations nous mènent à une conclusion très intéressante : la minimisation conjointe de la puissance et du délai n'est pas équivalente à une maximisation de l'efficacité énergétique du réseaux.

En raison de complexité de calcul du problème de minimisation de la puissance et du délai, nous proposons un algorithme heuristique glouton. Notre objectif est de proposer une solution efficace applicable pour les implémentations pratiques. L'heuristique proposée a pour but de calculer le niveau de la puissance d'émission des BSs déployés dans le réseau et à rattacher les utilisateurs à ces stations de base d'une manière qui minimise conjointement la puissance globale du réseau et le délai de transmission globale du réseau. Nous décomposons donc le problème de minimisation de la puissance et du délai en deux sous-problèmes, (i) problème du mode de fonctionnement de BS et (ii) le problème de rattachement des utilisateur. Dans le premier problème, l'heuristique commence par un état du réseau initial où toutes les stations de base transmettent au niveau de puissance le plus élevé. Ensuite, l'heuristique change de façon itérative le niveau de puissance d'émission de stations de base candidates. Dans le deuxième problème, l'heuristique cherche à associer les utilisateurs avec la meilleur BS. Cela se fait à chaque changement d'un niveau de puissance d'émission d'une BS. La sélection de la meilleure BS prend en compte le débit crête des utilisateurs et le nombre des utilisateur qui sont couverte par la BS. L'algorithme heuristique s'arrête lorsqu'il n'y a plus d'amélioration qui peut être obtenue en termes de minimisation de la puissance et du délai.

Les résultats de simulation montrent que l'heuristique proposée donne une réduction de la puissance consommée de l'ordre de 45% par rapport aux réseaux existants.

Les publications directement liées à contributions sont les suivants :

- Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, A Heuristic Algorithm for Joint Power-Delay Minimization in Green Wireless Access Networks, in *International Conference on Computing, Networking and Communications (ICNC), Workshop on Computing, Networking and Communications (CNC)*, Anaheim, USA, 2015.
- Farah Moety, Samer Lahoud, Kinda Khawam and Bernard Cousin, Joint Power-Delay Minimization in Green Wireless Access Networks, *IEEE Personal, Indoor and mobile radio Communications (IEEE PIMRC)*, London, United-Kingdom, 2013.
- Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, Power-Delay Tradeoffs in Green Wireless Access Networks, in *Vehicular Technology Conference (VTC FALL 2013)*, Las Vegas, USA, 2013.

0.4 Minimisation conjointe de la puissance et du délai dans les réseaux les réseaux 4G sans-fil

Dans la deuxième partie de la thèse, nous nous concentrons sur les compromis entre puissance et délai dans les réseaux 4G sans-fil. En particulier, nous couvrons la technologie LTE considérant le modèle du projet EARTH [1, 2] pour celui de la puissance de BS et le modèle de partage des temps équitable (*fair-time sharing*) pour l'allocation des ressources radio. Plus précisément, nous considérons un système de partage équitable en temps car il correspond à l'Orthogonal Frequency Division Multiple Access (OFDMA) largement utilisé dans la technologie LTE avec un ordonnanceur Round Robin. Cette politique de partage des ressources assure l'équité temporelle, ce qui signifie que tous les utilisateurs obtiennent statistiquement un nombre similaire d'intervalles de temps. A partir d'une formulation non-linéaire binaire du problème, nous transformons le problème de minimisation de la puissance et du délai en un problème de programmation mixte linéaire en nombres entiers. Nous étudions différents paramètres de préférence qui permettent d'évaluer le compromis entre la puissance consommée et la délai de transmission. Nous considérons des déploiements ruraux et urbains, et nous avons ainsi évalué l'impact de la position de l'utilisateur final dans la cellule sur les compromis obtenus. Pour un réglage adéquat des poids associés, soit à la puissance consommée, soit au délai de transmission, notre approche d'optimisation réduit la consommation de puissance de 4% et le délai de transmission de 8% par rapport aux réseaux existants. En outre, nous montrons que les économies de puissance dépendent principalement de la distribution des utilisateurs dans le réseau et aussi de la puissance consommée en mode veille.

Ensuite, nous étudions le cas d'un réseau LTE réaliste. La défi majeur, qui se pose dans ce cas, est la haute complexité de calcul nécessaire pour obtenir la solution optimale. Par conséquent, nous proposons une heuristique basée sur la méthode de recuit simulé pour le problème de minimisation conjointe de la puissance et du délai. Notre heuristique commence avec une solution réalisable initiale aléatoire pour le mode de fonctionnement de BS et de le rattachement des utilisateurs. Cette solution détermine le coût global du réseau. Ensuite, à chaque itération, une BS est choisie au hasard pour changer son niveau de puissance d'émission qui est choisie de manière uniforme à partir des niveaux de puissance disponibles. A chaque changement de la BS niveau de transmission de puissance, les utilisateurs sont raccordés à la meilleure BS. Cette solution est une solution candidate pour être utilisée, et son coût global du réseau est calculé. La solution candidate est acceptée en tant que solution courante sur la base d'une probabilité prédéfinie. Typiquement, les étapes sont répétées jusqu'à ce qu'un critère d'arrêt donnée est satisfait. On note que la sélection de la meilleure BS prend en compte le débit crête des utilisateurs et le nombre des utilisateur qui sont couverte par la BS.

Les paramètres les plus importants qui contrôlent la progression de l'algorithme de recuit proposé sont les suivants : le nombre maximal d'itérations de l'algorithme. Le paramètre de précision indiquant si la solution actuelle est améliorée par rapport à la précédente. Enfin, une constante positive qui détermine la probabilité d'acceptation de la solution candidate.

Nous montrons que l'heuristique proposée offre une solution proche de l'optimal et surpasse les approches existantes en termes de réduction du coût du réseau. De plus, notre heuristique permet une économie de puissance pouvant aller jusqu'à 18% et une réduction de délai pouvant aller jusqu'à 32% pour un temps de calcul raisonnable.

Les publications directement liées à ces contributions sont les suivants :

- Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, Joint Power-Delay Minimization in 4G Wireless Networks, in *Wireless Days*, Rio de Janeiro, Brazil, 2014.
- Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, Optimization Models for the Joint Power-Delay Minimization Problem in Green Wireless Access Networks, *submitted to Computer Networks*, 2014.

0.5 Conclusion

Les besoins énergétiques croissants, la diminution croissante des ressources énergétiques traditionnelles, avec la hausse du trafic de l'Internet mobile, tous appellent à des solutions pour relever le défi des réseaux d'accès sans-fil à faible consommation d'énergie. Cette thèse étudie le problème difficile de l'économie de la puissance consommée et délai de transmission minimisation dans les réseaux sans-fil. Précisément, le but est de trouver le meilleur compromis possible entre la réduction du nombre de stations de base actives et le réglage de la puissance d'émission de ceux qui restent actives tout en sélectionnant la meilleure rattachement des utilisateurs donnant les plus faibles délais de transmission des utilisateurs. Nous avons couvert deux réseaux sans-fil différents en raison de leur pertinence : les réseaux locaux sans-fil (IEEE 802.11 WLAN) et les réseaux cellulaires dotés de la technologie LTE. Tout d'abord, nous avons étudié les approches existantes qui ont été considérées dans la littérature pour améliorer l'efficacité énergétique des réseaux d'accès sans-fil. Dans la première partie de cette thèse, nous avons traité le problème de la minimisation conjointe de la puissance et du délai dans les réseaux WLAN. Nous avons formulé ce problème comme un problème de programmation mixte linéaire en nombres entiers. Nous avons étudié différents paramètres de préférence qui permettent d'évaluer le compromis entre la puissance consommée et la délai de transmission. Les résultats montrent que, pour une minimisation de la puissance, on obtient des économies de puissance pouvant aller jusqu'à 16%, alors que pour un cas de minimisation du délai, on obtient une réduction de délai de l'ordre de 6%. De

plus, les résultats de simulations nous mènent à une conclusion très intéressante : la minimisation conjointe de la puissance et du délai n'est pas équivalente à une maximisation de l'efficacité énergétique du réseaux.

En raison de complexité de calcul du problème de minimisation de la puissance et du délai, nous avons proposé un algorithme heuristique glouton qui donne une réduction de la puissance consommée de l'ordre de 45% par rapport aux réseaux existants.

Dans la deuxième partie de la thèse, nous avons étudié le problème de la minimisation conjointe de la puissance et du délai dans les réseaux 4G sans-fil. Pour un réglage adéquat des poids associés, soit à la puissance consommée, soit au délai de transmission, notre approche d'optimisation réduit la consommation de puissance de 4% et le délai de transmission de 8% par rapport aux réseaux existants. En outre, nous montrons que les économies de puissance dépendent principalement de la distribution des utilisateurs dans le réseau et aussi de la puissance consommée en mode veille.

Finalement, nous avons proposé une heuristique basée sur la méthode de recuit simulé pour le problème de minimisation conjointe de la puissance et du délai. L'heuristique proposée offre une solution proche de l'optimal et surpasse les approches existantes en termes de réduction du coût du réseau. De plus, notre heuristique permet une économie de puissance pouvant aller jusqu'à 18% et une réduction de délai pouvant aller jusqu'à 32% dans un cas d'un réseau LTE réaliste.

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When we are no longer able to change a situation, we are challenged to change ourselves.

Viktor E. Frankl,
Man's Search for Meaning

In recent years, global energy consumption has become a major issue, because of its significant environmental footprint and eventual exhaustion of traditional energy resources. Information and Communication Technology (ICT) accounts for around 3% of the world's annual electrical energy consumption and 2% of total carbon emissions [6]. Moreover, it is estimated that ICT energy consumption is rising at 15 to 20 % per year, doubling every five years [7]. In 2008 this corresponded to about 60 billion kWh of electrical energy consumption and about 40 million metric tons of CO₂ [8]. As a branch of the ICT sector, wireless access networks are responsible for 0.5% of this consumption and about 0.2% of these emissions [9]. In addition to the environmental impacts, mobile operators are interested in reducing energy consumption for economic reasons. Precisely, the cost of running a network is largely affected by the energy bill and significant savings in capital expenditure and operational expenditure can be realized through reduced energy needs [10]. Moreover, mobile data traffic has grown at a compound annual growth rate of 131 % between 2008 and 2013, and has exceeded two exabyte per month in 2013 [11]. Such an increase of the data traffic brings the need of additional network capacity along with the network infrastructure to support it. This implies larger money investments from the operators to provide such an infrastructure as well as higher energy consumption. All of this calls for green solutions to address the challenges in energy-efficient communications. In this regards, several research projects have been developed to work on the energy-efficiency issues from different approaches. Table 1.1 lists some major international projects on green radio. For instance, Optimizing Power Efficiency in Mobile Radio Networks (OPERA-NET) [12], is a European research project, that wants to improve the energy efficiency by 20% by 2020. In the United Kingdom, Green Radio has been among Core 5 Pro-

grams in Mobile VCE [13] since 2009. It sets the ambitious goal of achieving a 100-fold reduction in power consumption over current wireless communication networks. Energy Aware Radio and Network Technologies (EARTH) [2], is one of the integrated projects under European Framework Program 7 (FP7). It aims at reducing the energy use of mobile cellular networks by a factor of at least 2. Towards Real Energy-efficient Network Design (TREND) [14] is also another European initiative with a holistic approach, that focuses on studying all the network sections (*i.e.*, User Equipments (UEs), core, access network and servers, etc.). Most recently, GreenTouch [15] sets its research goal to deliver the architecture and specification needed to reduce energy consumption per bit by a factor of 1000 from the current level by 2015 [5].

Table 1.1: International research projects related to green radio[5]

Project name	OPERA-NET 1-2	Green Radio	EARTH	TREND	Green Touch
Duration	2008-2011 2011-2015	2009-2012	2010-2012	2010-2013	2010-2015

Currently, over 80% of the power in mobile telecommunications is consumed by the radio access network, more specifically at the base station (BS) level [10]. Hence, many research activities focus on improving the energy efficiency of wireless access networks. We classify these activities according to different approaches that run at different timescales.

Planning and deployment: The planning of energy-efficient wireless networks and the deployment of energy-aware BSs deal with the problem of determining the positioning of BSs, the type (*e.g.*, macro, micro, pico or femto) and the number of BSs needed to be deployed. In this context, we notice that heterogeneous networks have gained great attention in current research. Precisely, deploying small and low-power BSs co-localized with macro cells is believed to decrease power consumption compared to high-power macro BSs [16, 17, 18]. It extends the coverage area of the macro BS where signals fail to reach distant UEs. Furthermore, small cells increase the network capacity in areas with very dense data usage. Planning and deployment tasks are performed at a large timescale, ranging from a few months to possibly years.

Cell sizing: Also known as cell breathing, cell sizing is a well-known concept that enables balancing traffic load in cellular telephony [19, 20]. When the cell becomes heavily loaded, the cell zooms in to reduce its coverage area, and the lightly loaded neighboring cells zoom out to accommodate the extra traffic. Many state-of-the-art techniques are used to implement cell sizing, such as adjusting the transmit power of a BS, cooperating between multiple BSs, and using relay stations and switching BSs to sleep mode [21]. These techniques are summarized as follows [21]:

- *Physical Adjustment:* By increasing/decreasing the transmit power of BS, or by adjusting

the antenna height and antenna tilt of BSs, cells can zoom out/in. Such adjustments need the help of additional mechanical instruments.

- *BS Cooperation*: Multiple BSs can cooperate with each other to communicate with the UE. By this cooperation, a new cell is formed from the UE's perspective, and its size englobes the original size of all the cooperating BSs. In 3GPP Long Term Evolution-Advanced (LTE-A), this technique is named as Coordinated Multi-Point (CoMP) transmit/receive.
- *Relaying*: Relay Stations (RSs) are deployed in cellular networks to improve the performance of cell-edge UEs. In this technique, the cell with RSs zooms out to reduce the power levels needed by UEs for uplink transmission.
- *BS Switching*: When a BS is switched to sleep mode, the air-conditioner and other energy consuming equipments can be switched off. In this case, the neighbor cells will zoom out to guarantee the coverage.

Cell sizing is performed at a medium timescale, ranging from hours to days.

User Association: User association is the functionality devoted to deciding the BS (macro, micro, pico or femto) with which a given UE will be associated in the network [22, 23]. User association is impacted by the cell sizing tasks: when an active BS is switched to sleep mode or changes its transmit power level, UEs may need to change their associations. Many metrics are considered for selecting the serving BS, such as the received signal quality (Signal-to-Noise Ratio (SNR) or the corresponding achievable rate), the traffic load, or the distance between BS and UE, etc. User association is performed at a small timescale, ranging from seconds to minutes.

Scheduling: Scheduling algorithms allocate the radio resources in wireless access networks, where the objectives consist of improving the network throughput, satisfying the delay constraints of real-time traffic, or achieving fair resource distribution among UEs. Energy-efficient schedulers are developed to reduce the network energy consumption while considering the aforementioned objectives. Scheduling is performed at millisecond timescale.

Reducing power consumption in wireless networks should consider the Quality of Service (QoS) requirements (such as delay, blocking probability, etc.). As these objectives are conflicting, a tradeoff becomes ineluctable. Chen *et al.* [5] identified four key tradeoffs of energy efficiency with network performance:

- deployment-energy efficiency to balance the deployment cost, throughput, and energy consumption in the network as a whole;
- spectrum-energy efficiency to balance the achievable rate and energy consumption of the network;
- bandwidth-power to balance the utilized bandwidth and the power needed for transmission;

- delay-power to balance the average end-to-end service delay and average power consumed in transmission.

The delay-power tradeoff has not been studied deeply in the literature except for in a few recent cases [24]. In this thesis, we address the multi-objective optimization problem of power saving and transmission delay minimization in wireless access networks. Specifically, power saving is achieved by adjusting the operation mode of the network BSs from high transmit power levels to low transmit power levels, or even sleep mode. In this context, changing the operation mode of the BSs is coupled with optimized user association. Such coupling makes solving the problem more challenging. Minimizing the transmission delay is achieved by selecting the best user association with the network BSs.

State-of-the-art power saving approaches can also be performed in Wireless Local Area Networks (WLANs). Although power consumption of a cellular network BS is much higher than that of a WLAN Access Point (AP), the large number of APs deployed in classrooms, offices, airports, hotels and malls, contributes to a rapid increase in the power consumption in wireless access networks. Hence, efficient management of the power consumed by a WLAN is an interesting challenge. In this thesis, we cover two different wireless networks: IEEE 802.11 WLANs [25] and cellular networks with Long Term Evolution (LTE).

1.1 Scope and Contributions of the Thesis

1.1.1 Scope of the Thesis

Targeting energy-efficiency while considering network performance is one of the most challenging problems in wireless access networks. In this thesis, we investigate the Power-Delay minimization problem and solve the following issues:

- How to optimize the conflicting metrics of power and delay in wireless access networks? What is the optimal BS operation mode and optimal user association that jointly minimizes the network power consumption and UE transmission delays?
- Solving the optimization problem of power and delay is very challenging due to highly complex coupling of BS operation mode and user association. Are there efficient algorithms that have low computational complexity and perform near optimally? Are there algorithms with original solutions that can be applied for real scenarios?

1.1.2 Main Contributions

This thesis answers exactly the above asked questions. In the following, we summarize our main contributions:

- We formulate the multi-objective optimization problem of power saving and delay minimization in wireless access networks, going beyond prior work which has focused on either minimizing energy without considering the delay minimization [10, 26, 27, 28, 29], or on delay analysis without accounting for energy minimization [23, 22]. Hence, the novelty in our approach is that it does not only strive to save energy by reducing the network power consumption, but also considers the minimization of the transmission delay.
- Unlike most of the literature studies, we combine different green approaches (BS on/sleep mode, adjustment of BS transmit power, user association) retaining advantages of each approach in order to provide power saving while minimizing transmission delay. Precisely, the proposed approach aims to optimally adjust the operation mode of the network BSs from high transmit power levels to low transmit power levels, or sleep mode, and optimally associates UEs with the network BSs in order to minimize the two objectives.
- We cover two different wireless networks: IEEE 802.11 WLANs and cellular networks with LTE. To the best of our knowledge, our formulation is the first one that captures the specificity of each technology in terms of the power model and radio resource allocation (fair-rate sharing and fair-time sharing). In the WLAN scenario, considering the fair-rate scheduling, the delay model provided is a unique feature of our work, and it is a realistic model used in IEEE 802.11 WLANs [30, 23, 22] compared to the pessimistic bound on the queuing delay model frequently adopted in the literature. In the LTE scenario, we consider a flat channel model with fair-time scheduling.
- To solve the multi-objective optimization problem, we resort to the weighted sum method by combining the multiple objectives into a single scalar objective function. This method allows us to investigate the power-delay tradeoffs by tuning the weights associated with each objective. This is an important feature of our model that allows it to reflect various preferences.
- Starting from a binary non-linear formulation of the problem, we provide a Mixed Integer Linear Programming (MILP) formulation of the problem that makes it computationally tractable. We thus compute the optimal solution of the Power-Delay minimization problem for both WLAN and LTE scenarios. When adequately tuned, our optimization approach shows significant power saving and delay reduction compared with legacy networks.
- Due to computational complexity issues, we propose two novel heuristic algorithms for the Power-Delay minimization problem in wireless access networks. In particular, in the

WLAN scenario, we propose a greedy heuristic algorithm for the considered problem. In the LTE scenario, we propose a Simulated Annealing (SA) based heuristic algorithm, and apply it on a realistic LTE deployment. The proposed heuristics aim to compute the transmit power level of the network BSs and associate UEs with these BSs in a way that jointly minimizes the network power consumption and transmission delay. The proposed algorithms have a low computational complexity which makes them advantageous compared with the optimal scheme. Moreover, the heuristic algorithms perform near to optimally and outperform the existing approaches.

1.2 Outline of the Thesis

The remainder of the thesis is organized as follows. The latest research in green wireless networks is surveyed in Chapter 2. We present the relevant performance metrics in green wireless networks and classify the different studied approaches to improve the energy efficiency of wireless access networks. Chapter 3 introduces our Power-Delay multi-objective optimization approach in wireless access networks. Resorting to the weighted sum method to solve the multi-objective minimization problem, we provide challenging techniques for the normalization of the objective functions.

Chapter 4 and 5 address the joint Power-Delay minimization in IEEE 802.11 WLANs. In the former chapter, we provide a Mixed Integer Linear Programming formulation of the problem. Moreover, we compute optimal power-delay tradeoffs and reveal the impact of the network topology on these tradeoffs. In Chapter 5, we propose a greedy heuristic algorithm for the problem and compare the performance of the proposed solution with the optimal scheme and the approaches adopted in legacy networks. Chapter 6 and Chapter 7 address the same problem in 4G wireless networks in LTE networks. The former chapter provides optimal power-delay tradeoffs considering urban and rural deployments. We assess the impact of the UE's position in the cell on the achievable tradeoffs. The latter chapter provides a simulated annealing based heuristic algorithm for the problem considering a realistic LTE deployment. We prove the effectiveness of the proposed SA solution in reducing both the total network cost and computational complexity.

Finally, we conclude this thesis and present some axes to be developed in future work in Chapter 8.

Research Approaches in Green Wireless Access Networks

In the past years, operators have focused on technological developments to meet capacity and user QoS demands. Recently, pushed by the needs to reduce energy, mobile operators are rethinking their network design for optimizing its energy efficiency while still satisfying the QoS requirements. In this context, several overview and survey papers have been written on the topic. Hasan *et al.* [6] presented a survey of methods to improve the power efficiency of cellular networks. The authors discussed metrics used to measure the energy efficiency of wireless networks. Then, they focused on techniques to obtain energy savings at the base station side, and in heterogeneous network deployments based on micro, pico and femto cells. They also discussed the benefits of using cognitive radio and cooperative relays technologies to enable green communication in cellular systems. Feng *et al.* [31] reviewed energy efficient solutions in wireless networks. The authors started by presenting energy-efficient metrics. Then, they focused on energy-efficient network resource management and on deployment strategies including heterogeneous networks and cooperative communications. Advanced physical layer techniques such as multiple-input multiple-output (MIMO) and orthogonal frequency division multiplexing (OFDM) have been also introduced to improve the energy efficiency of wireless networks. Suarez *et al.* [32] provided an overview and classification of research approaches in green wireless networks, where the main research directions presented are: the component level research, the cell layout adaptation, the radio resource management and the cognitive radio. Another survey on green base stations in cellular networks was provided in [33]. The authors discussed several solutions to minimize the BS energy consumption by devising energy efficient hardware design, power saving protocols for sleep modes, energy aware cooperative base station power management with self organizing cells, and by using renewable energy sources. A recent survey on the challenges for achieving sustainable cellular net-

works was presented in [34]. Energy consumption models, fundamental trade-offs, green metrics, and energy-aware management strategies were critically discussed.

In this chapter, we provide an overview on the latest research in green wireless networks. First, we present the different performance metrics studied in the literature to evaluate both the energy consumption and QoS performance of wireless networks; we also put forward the metrics characterizing the tradeoffs between the aforementioned conflicting objectives. Second, we provide a survey on the different approaches that have been considered in the literature to improve the energy efficiency of wireless access networks. We present these approaches according to the classification provided in Chapter 1. Finally, we discuss the novelties and similarities of our work with the most related prior work.

2.1 Performance Metrics in Green Wireless Networks

There are several questions that come to mind in order to address the problem at hand; first, how do we measure the degree of greenness in wireless networks? and second, which network QoS performance metrics should be considered in this context? In this section, we provide the relevant state-of-the-art performance metrics used to assess energy saving and network performance. The *energy consumption metrics* are Power consumption (P [W]), Energy consumption (E [J]), and Area Power Consumption (APC [W/m^2]). APC [10] is defined as the average power consumed in a cell divided by the corresponding cell area.

Reducing energy consumption in wireless networks is coupled with satisfying required *QoS performance metrics*. The different *QoS performance metrics* are Throughput (Th [bit/s]), Delay or Transmission Delay (D [s]), Blocking Probability (BP [%]), Area Throughput (ATh [bit/s/ m^2]) [26], and Area Spectral Efficiency (ASE [bit/s/Hz/ m^2]). ASE [35] is defined as the summation of the spectral efficiency over a reference area. Coverage (Cov) and capacity (Cap) are also used in the literature. For instance, when planning an energy-efficient wireless network, the coverage constraint can be expressed in terms of the minimum achievable bit-rate at the cell edge, while the capacity constraint can be expressed in terms of the maximum load at a BS.

Finally, the *tradeoff metrics* are used to evaluate the tradeoff between energy consumption and QoS performance and include Energy Efficiency (EE [bit/Joule] or [bit/s/Watt]) and Area Energy Efficiency (AEE [bit/Joule/ m^2]). EE is defined as the average data rate provided by the network over the power consumption of the BSs. AEE [27] is defined as the EE over the area covered by the network BSs.

2.2 Approaches in Green Wireless Networks

In this section, we provide different studies on cellular networks and WLANs according to the classification presented in Chapter 1. We start with the planning and deployment approaches. Then, we present studies on the cell sizing approach coupled with the user association approach. Finally, we put forward the scheduling approach.

2.2.1 Planning and Deployment

In the planning and deployment approach, topology-specific design perspectives and improved planning methodologies were developed to improve power efficiency. Different network deployment strategies have been investigated [10, 27, 26]. The idea of deploying small, low-power micro BSs alongside with macro sites was exploited to reduce the energy consumption of cellular radio networks [10, 27]. Simulation results [10] showed that the power savings obtained from such deployments depend strongly on the offset of site power (both macro and micro). In fact, this offset accounts for the power consumed in BSs independently of the average transmit power. Traffic is assumed to be uniformly distributed [10, 27]. Tombaz *et al.* [26] introduced WLAN APs at the cell border and investigated the improvements in energy efficiency improvements through different heterogeneous networks for both uniform and non-uniform traffic distribution scenarios. Simulations showed that the heterogeneous network composed of macro BSs and WLAN APs gives the best energy efficiency results due to the low power consumption of APs. Moreover, an energy-efficient deployment strategy highly depends on the area throughput demand. For instance, for a high area throughput target, heterogeneous deployments are more energy efficient than a network composed of only macro BSs.

However, in these deployment strategies, the network configuration is fixed, even if the network may be composed of various types of BS. Precisely, at the planning/deployment stage of the network, cell size and capacity are usually fixed based on the estimation of peak traffic load. Traffic load in wireless networks can have significant spatial and temporal fluctuations due to user mobility and the bursty nature of mobile applications [36]. Therefore, many studies have investigated the effects of switching off BSs in consideration of traffic fluctuations in wireless networks. Eunsung *et al.* [28] proposed a basic distributed algorithm for dynamically switching off BSs to reduce network energy consumption, considering the variation of traffic characteristics over time. The results showed that the energy saving not only depends on the traffic fluctuations, but also on the BS density. Traffic is considered to be homogeneous among all BSs. In another approach [29], the coverage planning in cellular networks was studied while taking into account sleep mode

for saving energy. The results showed that with a careful design of the inter-cell distance, the network energy consumption can be reduced. The authors only took into account the coverage constraints while overlooking the capacity constraints. A joint design and management optimization approach of cellular networks allowed for the adjustment of tradeoffs between the installation cost, operational cost, and connection quality cost by tuning weighting factors for each cost [37]. Moreover, BSs are switched on and off to dynamically adapt the network capacity to the traffic load without violating coverage constraints. The results showed that including energy cost in the operational cost and considering energy management strategies at the design stages produce more energy-efficient topologies than when only installation cost is considered. Micallef *et al.* [38] explored different features of BS sleep modes during hours of low traffic. These features can vary by switching to sleep mode, the entire site, some of the site sectors, or some of the carriers for a given technology. This was applied to different network topologies, macro-only based networks, and a set of heterogeneous networks employing the use of small cells in traffic hotspots. Using Markov Decision Processes (MDPs), Saker *et al.* [39] proposed a centralized optimal sleep/wake-up mechanism for macro/femto heterogeneous networks. When the cell is not highly loaded and the macro BS can alone handle the traffic while offering users satisfactory QoS, the femto cells are switched off. When the load increases, one or more femto cells are selected to be switched on depending on the load and localization of traffic. The UE QoS is measured as the proportion of UEs that have a throughput higher than a given threshold.

2.2.2 Cell Sizing and User Association

The concept of cell sizing (zooming or breathing) by integrating BS switching was introduced in [21]. The authors proposed centralized and decentralized cell zooming algorithms based on the transmission rate requirements of the UEs and the capacity of the BSs. The results showed that the algorithms save a large amount of energy when traffic load is light, and that they can leverage the tradeoff between energy consumption and outage probability. Bahl *et al.* [40] proposed cell breathing algorithms for WLANs that attempt to maximize the overall system throughput; results showed that this throughput is improved for both uniform and non uniform distribution. Lorincz *et al.* [41] derived ILP models to minimize the network power consumption in WLANs while ensuring coverage of the active UEs and sufficient capacity for guaranteeing QoS. The optimization consists of switching on/off APs and adjusting their transmit power according to the traffic pattern during the day. Moreover, UEs are associated with BSs according to bandwidth requirements. The results showed significant savings in the monthly network energy consumption when optimized network management based on UE activity is implemented. By assuming that

the inter-cell interference is static, Son *et al.* [24] formulated a minimization problem that allows for a flexible tradeoff between flow-level performance and energy consumption. UEs are associated with BSs so as to minimize the average flow delay, and greedy algorithms were proposed for switching the network BSs on and off. The results showed that the user association and greedy algorithms can reduce the total energy consumption, depending on the arrival rate of the traffic, its spatial distribution and the density of BS deployment. The case where BSs switch between on and off modes without adjusting their transmit power was investigated.

A distributed pricing-based algorithm that assigns UEs to BSs and adjusts the transmission power in a way that minimizes the network energy expenditure was proposed in [42]. The main idea of the algorithm is to decrease the power price until all of the UEs are associated with the network BSs. The algorithm provides significant energy savings compared with a nearest-BS algorithm. For the LTE-Advanced standard, a greedy heuristic algorithm was proposed to switch off a BS according to the average distance of its UEs, thus neglecting the actual traffic load [43]. The algorithm minimizes the energy consumption of the network without compromising the QoS in terms of the outage probability of the UEs.

An energy-efficient algorithm was proposed for cellular networks based on the principle of cooperation between BSs [44]. In this algorithm, the BSs dynamically switch between active/sleep modes depending on the traffic situation. Another study [45] used deterministic patterns for switching BSs through mutual cooperation among BSs. QoS is guaranteed by focusing on the worst-case transmission/reception location of the UE situated in the switched-off cell. Given the amount of time required to switch on/off a BS, focus in [46] was directed toward the design of base-station sleep and wake-up transitions, which led to a progressive BS switching off and on, respectively. The results under realistic test scenarios showed that these transitions are promptly operated, allowing BSs to be switched on and off within a short time.

2.2.3 Scheduling

In the scheduling approach, energy-efficient schedulers were developed to reduce the network energy consumption while maintaining a satisfactory service for the end UEs. Videv *et al.* [47] developed a scheduler with aims of solving the problem of energy-efficient resource allocation in Orthogonal Frequency Division Multiple Access (OFDMA) cellular systems. The results showed that energy savings are achieved with no detriment to UE satisfaction in terms of achieved data rate. Chen *et al.* [48] proposed an energy-efficient coordinated scheduling mechanism to reduce the energy consumption in cellular networks. This is done by dynamically switching off the component carrier feature specified in LTE-A systems and BSs according to load variations, while

maintaining service continuity for UEs. Holtkamp *et al.* [49] proposed a scheduling algorithm that aims to minimize the base station power consumption for the downlink of multiuser MIMO-OFDM. The proposed algorithm finds the number of transmit antennas, the transmit power per resource unit and spatial channel, the number of discontinuous transmission time slots, and the multiuser resource allocation, such that supply power consumption is minimized.

Tables 2.1 and 2.2 show a survey of recent papers that studied greening approaches and algorithms in wireless networks, with focus on the metrics used for energy consumption and QoS performance.

2.3 Novelties compared with related work

In this section, we discuss the novelties and similarities with the most related prior work. The optimization approach proposed by Lorincz *et al.* [41] does not support the feature of tuning the weights associated to the power and the network QoS performance. Moreover the authors considered the theoretical data rate of the IEEE 802.11g, which is a pessimistic bound compared to the effective data rate we use in this thesis. In fact, the approach in [41] differs from our work by guaranteeing to each UE a predefined demand. Besides, assuming that UEs occupy fixed positions in the cell (called Test Points (TPs)), the coverage and capacity are only needed for these TPs rather than for the full area. Each TP is considered as a traffic centroid where a given amount of traffic (usually measured in bit/s or in Erlang) is requested. This is a discrete modeling of the traffic, which has been originally proposed in [50].

Compared with the work in [24], the delay is computed using the M/GI/1 queue, which is also a pessimistic bound on delay compared to the realistic delay model we use. Moreover, the authors studied only the case where BSs switch between on/off modes without adjusting the transmit power. Unlike the previous mentioned work, the authors considered a continuous modeling of the traffic, in other words, the traffic is modeled for each point of the service area.

In this thesis, we adopt the discrete modeling of the traffic which is adopted by basically most literature on radio coverage [51].

Table 2.1: Classification of approaches in green wireless networks (a)

		[10]	[27]	[26]	[28]	[29]	[37]	[21]	[41]
Green Approaches	Planning	-	-	-	-	✓	✓	-	-
	Deployment (Macro and micro, pico, or AP)	micro	pico	micro, pico, AP	-	-	micro, pico	-	-
	BS On/Sleep/Off	-	-	-	✓	✓	✓	✓	✓
	Adjustment of BS transmit power	-	-	-	-	✓	✓	✓	✓
	CoMP	-	-	-	-	-	-	-	-
	User association	-	✓	✓	-	-	✓	✓	✓
	Scheduling	-	-	-	-	-	-	-	-
Metrics	Energy Consumption <i>E, P or APC</i>	<i>APC</i>	<i>APC</i>	<i>APC</i>	<i>E</i>	<i>APC</i>	<i>E</i>	<i>E</i>	<i>E, P</i>
	QoS Performance <i>Th, D, BP, ATh, ASE</i> <i>Cov or Cap</i> (cf. Section 2.1)	- <i>ASE</i> ✓ ✓	- - ✓ ✓	- <i>ATh</i> ✓ ✓	<i>BP</i> - - ✓	- - ✓ -	- - ✓ ✓	<i>BP</i> - ✓ ✓	- - ✓ ✓
	Tradeoffs <i>EE or AEE</i>	-	<i>EE, AEE</i>	-	-	-	-	-	-
	Optimization	-	-	-	✓	✓	✓	-	✓
	Heuristic	-	-	-	✓	✓	-	✓	-
Solution Approach	Analytic	-	-	-	-	✓	-	-	-
	Cellular	✓	✓	✓	✓	✓	✓	✓	-
	LTE or LTE-A	✓	✓	-	-	-	-	-	-
	WiMAX	-	-	-	-	-	-	-	-
	2G/3G	-	-	3G	-	-	GSM	-	-
Network and Technology Application	WLAN	-	-	-	-	-	-	-	✓

Table 2.2: Classification of approaches in green wireless networks (b)

		[24]	[42]	[43]	[44]	[45]	[47]	[48]
Green Approaches	Planning	-	-	-	-	-	-	-
	Deployment (Macro and micro, pico, or AP)	micro	-	-	-	-	-	-
	BS On/Sleep/Off	✓	✓	✓	✓	✓	-	✓
	Adjustment of BS transmit power	-	✓	✓	✓	✓	✓	✓
	CoMP	-	-	-	✓	✓	-	-
	User association	✓	✓	✓	-	✓	✓	✓
	Scheduling	-	-	-	-	-	✓	✓
Metrics	Energy Consumption <i>E, P or APC</i>	<i>P</i>	<i>P</i>	<i>P</i>	-	<i>P</i>	<i>P</i>	<i>P</i>
	QoS Performance <i>Th, D, BP, Ath, ASE, Cov or Cap</i> (cf. Section 2.1)	<i>D</i> - ✓ ✓	- - ✓ ✓	<i>BP</i> - ✓ -	- - - ✓	<i>BP</i> - ✓ -	<i>Th</i> - ✓ ✓	<i>Th, ASE</i> - ✓ ✓
	Tradeoffs <i>EE or AEE</i>	-	-	<i>EE</i>	-	-		<i>EE</i>
	Optimization	✓	-	-	-	-	-	-
	Heuristic	✓	✓	✓	✓	✓	✓	✓
Solution Approach	Analytic	✓	-	-	-	-	-	-
	Cellular	✓	✓	✓	✓	✓	✓	✓
	LTE or LTE-A	-	-	-	-	-	✓	✓
	WiMAX	✓	-	-	-	-	-	-
	2G/3G	-	-	-	-	-	-	-
Network and Technology Application	WLAN	-	-	-	-	-	-	-

**Minimization of Power and
Delay in Green Wireless
Access Networks****3.1 Introduction**

In this chapter, we present the multi-objective optimization problem of power saving and delay minimization in green wireless access networks. Power saving is achieved by adjusting the operation mode of the network BSs from high transmit power levels to low transmit power levels, or even sleep mode. Minimizing the transmission delay is achieved by selecting the best user association with the network BSs. A key challenge is to find the optimal tradeoff between these two objectives. On the one hand, reducing the transmit power level of the BSs or switching them to sleep mode to save energy, may result in increasing the transmission delay. Precisely, if there are no coverage constraints, then all BSs could be in sleep mode, no UE is served, and the transmission delay becomes infinite. On the other hand, to minimize the transmission delay, each BS should transmit at the highest power level possible. We thus formulate the multi-objective power-delay minimization problem that enables to tune the predominance of each objective. Moreover, we provide two solution methods to the multi-objective optimization: the ϵ -constraints method and the weighted sum method. These methods are characterized by a single objective optimization. Furthermore, we discuss the major challenges faced after resorting to a single objective optimization.

The remainder of this chapter is organized as follows. In Section 3.3, we present the Power-Delay minimization problem formulation. In Section 3.4, we provide the solution methods from multi-objective optimization problem to single-objective optimization problem. Finally, we conclude in Section 3.5.

3.2 Definitions and Notations

Let us introduce some definitions to formally characterize some concepts used in this thesis. The *transmission delay* of a given UE is defined as the inverse of the throughput perceived by this UE. The *peak rate* of a given UE is defined as the throughput experienced by the UE when served alone in the cell. The peak rate of each UE depends on its received SNR from the serving BS. In fact, the SNR is an accurate indicator of the channel quality because it is affected by different parameters such as the transmit power of the serving BS, path loss, bandwidth, etc. The *coverage area* of a given BS is defined as the geographical area where the received SNR of each UE is above a given threshold. As the peak rate perceived by a given UE depends on its SNR, we thus consider that a UE is covered if it perceives a peak rate, from at least one BS, higher than a given peak rate threshold (χ_{th}).

We consider a wireless access network with N_{bs} BSs. we assume that each BS operates in two modes: active mode and sleep mode. N_l denotes the number of transmit power levels of a BS. Transmitting at different power levels leads to different coverage area sizes. The indexes $i \in I = \{1, \dots, N_{bs}\}$, and $j \in J = \{1, \dots, N_l\}$, are used throughout the paper to designate a given BS and its transmit power level, respectively. Note that for $j = 1$, we consider that the BS transmits at the highest power level, and for $j = N_l$, the BS is in sleep mode. We term by $k \in K = \{1, \dots, N_u\}$, the index of a given UE where N_u is the total number of UEs in the network. Let $T_{i,j,k}$ denote the transmission delay of UE k associated with BS i transmitting at power level j . Let $\chi_{i,j,k}$ denote the peak rate perceived by UE k from BS i transmitting at power level j .

3.3 Multi-objective Optimization Problem Formulation

Our approach is formulated as an optimization problem that consists of minimizing the power consumption of the network and the sum of the transmission delays of all UEs. The design variables in our Power-Delay minimization problem are as follows:

- The operation mode of the network BSs (on/sleep) and the corresponding transmit power level for active BSs.
- The users association with the network BSs.

Let Λ be the matrix, with elements $\lambda_{i,j}$, defining the operation mode of the network BSs; and $\lambda_{i,j}$ be a binary variable that indicates whether or not BS i transmits at level j .

$$\lambda_{i,j} = \begin{cases} 1 & \text{if BS } i \text{ transmits at power level } j, \\ 0 & \text{otherwise.} \end{cases}$$

Let Θ be the matrix, with elements $\theta_{i,k}$, defining the users association with the network BSs; and $\theta_{i,k}$ be a binary variable that indicates whether or not a UE k is associated with BS i .

$$\theta_{i,k} = \begin{cases} 1 & \text{if UE } k \text{ is associated with BS } i, \\ 0 & \text{otherwise.} \end{cases}$$

The constraints on the decision variables are:

$$\sum_{j \in J} \lambda_{i,j} = 1, \quad \forall i \in I, \quad (3.1)$$

$$\sum_{i \in I} \theta_{i,k} = 1, \quad \forall k \in K, \quad (3.2)$$

$$\lambda_{i,N_l} \theta_{i,k} = 0, \quad \forall i \in I, \forall k \in K, \quad (3.3)$$

$$\lambda_{i,j} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J, \quad (3.4)$$

$$\theta_{i,k} \in \{0, 1\}, \quad \forall i \in I, \forall k \in K. \quad (3.5)$$

Constraints (3.1) state that each BS transmits at only one power level. Constraints (3.2) ensure that a given UE is associated with only one BS. In practice, when BSs are in sleep mode, some UEs will be out of coverage. Thus, to prevent UEs from being associated with a BS in sleep mode, we add constraints (3.3). These equations ensure that λ_{i,N_l} and $\theta_{i,k}$ are not both equal to one. Indeed, when BS i is in sleep mode, λ_{i,N_l} is equal to one, so $\theta_{i,k}$ cannot equal one for all UEs. Constraints (3.4) and (3.5) are the integrality constraints for the decision variables $\lambda_{i,j}$ and $\theta_{i,k}$. To eliminate some trivial cases that must not be included in the solution, we add the following constraints:

- If UE k is not covered by BS i transmitting at the first (highest) power level, then

$$\theta_{i,k} = 0. \quad (3.6)$$

The equation (3.6) prevents a given UE from being associated with a BS if that UE is not in the BS first power level coverage area.

- If UE k is not covered by BS i transmitting at power level j , $j \in \{2, \dots, N_l - 1\}$, then

$$\lambda_{i,j} \theta_{i,k} = 0, \quad \forall j \in \{2, \dots, N_l - 1\}. \quad (3.7)$$

Equations (3.7) ensure that $\lambda_{i,j}$ and $\theta_{i,k}$ are not both equal to one, which prevents a given UE from being associated with a BS if the former is not in the BS's j^{th} power level coverage area.

The goal of our approach is to jointly minimize the total network power and the total network delay. Thus, the two objectives are:

1. The *total network power* is defined as the total power consumption of active BSs in the network. Let $p_{i,j}$ denote the average power consumed per BS i transmitting at power level j . The total network power, denoted by C_p , is given by:

$$C_p(\Lambda) = \sum_{i \in I, j \in J} p_{i,j} \lambda_{i,j}. \quad (3.8)$$

The minimization of the total network power aims at reducing the network power consumption.

2. The *total network delay* is defined as the sum of transmission delays (cf. Section 3.2) of all UEs in the network. $T_{i,j,k}$ being the transmission delay of UE k associated with BS i transmitting at power level j , the total network delay, denoted by C_d , is thus given by:

$$C_d(\Lambda, \Theta) = \sum_{i \in I, j \in J, k \in K} T_{i,j,k} \lambda_{i,j} \theta_{i,k}. \quad (3.9)$$

The minimization of the total network delay aims at selecting the best user association that incurs the lowest sum of data unit transmission delays.

The proposed multi-objective optimization problem denoted by Multiobj-Power-Delay-Min aims at computing the transmit power level of the BSs deployed in the network as well as associating UEs with these BSs in a way that jointly minimizes the total network power and the total network delay. Therefore, Multiobj-Power-Delay-Min is given by:

$$\begin{aligned} & \underset{\Lambda, \Theta}{\text{minimize}} && C_p(\Lambda), \\ & && C_d(\Lambda, \Theta), \\ & \text{subject to} && (3.1) \text{ to } (3.7). \end{aligned}$$

3.4 From Multi-objective Optimization to Single-objective Optimization

Solving a multi-objective optimization problem is a very challenging task. In this section, we provide two solution methods to multi-objective optimization: the ϵ -constraints method and the weighted sum method. Using these techniques, we obtain new optimization problems with a single objective function which are easier to solve than the original problems.

3.4.1 ϵ -Constraint Method

The ϵ -constraint method is based on minimizing one objective function and considering the other objectives as constraints bound by some allowable level ϵ_n . Hence, a single objective minimization is carried out subject to additional constraints on the other objective functions. In our

multi-objective optimization, since we have two objective functions, this method may be formulated in two variants presented in the following.

3.4.1.1 Power Minimization subject to Delay Constraints

The power minimization subject to delay constraints problem, denoted by Power-Min-Delay-Const, is given by:

$$\underset{\Lambda}{\text{minimize}} \quad C_p(\Lambda), \quad (3.10)$$

$$C_d(\Lambda, \Theta) \leq \epsilon_1, \quad (3.11)$$

subject to: (3.1) to (3.7).

ϵ_1 is a value of the total network delay that should not be exceeded. The Power-Min-Delay-Const problem can be literally expressed as: given some delay bound (constraint (3.11)), is there a BS operation mode and a user association satisfying constraints (3.1) to (3.7) such that the total network power, denoted by C_p , is minimized?

3.4.1.1.1 Delay Minimization subject to Power Constraints problem The delay minimization subject to power constraints problem, denoted by Delay-Min-Power-Const is given by:

$$\underset{\Lambda, \Theta}{\text{minimize}} \quad C_d(\Lambda, \Theta), \quad (3.12)$$

$$C_p(\Lambda) \leq \epsilon_2, \quad (3.13)$$

subject to: (3.1) to (3.7).

ϵ_2 is a value of the total network power that should not be exceeded. In other words, given some power bound (constraint (3.13)), is there a BS operation mode and a user association satisfying constraints (3.1) to (3.7) such that the total network delay, denoted by C_d , is minimized?

The major drawback of such problems is that the decision maker (*i.e.*, the network operator) cannot estimate the total network delay or the total network power. Thus, it is hard to choose the adequate bounds on the delay or the power.

3.4.2 Weighted Sum Method

The weighted sum method consists of summing the objective functions combined with different weighting coefficients. The multi-objective optimization problem is transformed into a scalar

optimization problem, denoted by Weighted-Sum-Power-Delay-Min:

$$\begin{aligned} & \underset{\Lambda, \Theta}{\text{minimize}} && C_t(\Lambda, \Theta) = \alpha C_p(\Lambda) + \beta \beta' C_d(\Lambda, \Theta), \\ & \text{subject to:} && (3.1) \text{ to } (3.7). \end{aligned} \quad (3.14)$$

where C_t denotes the *total network cost* defined as the weighted sum of the total network power and the total network delay. β' is a normalization factor that will scale the two objectives properly. α and β are the weighting coefficients representing the relative importance of the two objectives. It is usually assumed that $\alpha + \beta = 1$ and that α and $\beta \in [0,1]$. In particular, when α equals 1 and β equals 0, we only focus on the power saving. As α decreases and β increases more importance is given to minimizing the delay. By tuning the weighting coefficients, we obtain different points located on the Pareto frontier representing all the compromises between the two objectives. The weighting coefficients are also called tuning factors, as decision makers use them to fine-tune the model parameters to reflect their decision preferences.

3.4.3 Normalization factor computation: challenges

As it is hard to choose the adequate bounds on the delay or the power in the ϵ -Constraint method, we resort in the next chapters to the weighted sum method to study the tradeoffs between minimizing the power consumption of the network and minimizing the UE transmission delays in the network for both WLANs and 4G wireless networks.

A key challenge in the weighted sum method is the normalization of the objective functions. In fact, the normalization plays an important role in ensuring the consistency of the optimal solutions with the preferences taken by the decision maker. Precisely, as different objective functions can have different magnitude, the normalization of the objectives is required to get a Pareto optimal solution consistent with the weights assigned to each objective.

In [52], three different schemes for normalization are considered:

- Normalization by the magnitude of the objective function at the initial solution. Thus, in our case, the normalization factor β' is computed as follows, $\beta' = C_p(\Lambda^0)/C_d(\Lambda^0, \Theta^0)$ where Λ^0 is the initial operation mode of the BS and Θ^0 is the initial user association.
- Normalization by the minimum of the objective functions. Therefore, $\beta' = C_p^*/C_d^*$, where C_p^* and C_d^* are respectively obtained by minimizing each of the objective function C_p and C_d individually subject to the original constraints.
- Normalization by the difference of the optimal function values in the Nadir and Utopia points. This gives the length of the intervals where the objective functions vary within the Pareto optimal set.

The first two schemes have been proved to be ineffective because they lead to distorted scaling [52]. Therefore, in this thesis we consider the third normalization scheme. In fact, the ranges of the objective Pareto optimal set provide valuable information for the solution process. Next, we show how to compute the Nadir and Utopia points for a general example, then we consider the case of the Weighted-Sum-Power-Delay-Min problem.

3.4.3.1 Nadir and Utopia points

A weighted sum problem can be written in the following form:

$$\begin{aligned} & \underset{x}{\text{minimize}} && \sum_{q=1}^Q w_q f_q(x) \\ & \text{subject to} && x \in \Omega, \end{aligned} \quad (3.15)$$

where $\forall q = 1, \dots, Q$, $f_q : \mathbb{R}^n \rightarrow \mathbb{R}$ are the objective functions and $\Omega \subseteq \mathbb{R}^n$ is the feasible region. Moreover, $\forall q = 1, \dots, Q$, $w_q \geq 0$, and $\sum_{q=1}^Q w_q = 1$. Furthermore, $w_q = u_q \mu_q$, where u_q are the weighting factors and μ_q are the normalization factors. The Utopia point, is obtained by minimizing each of the objective functions individually subject to the original constraints. Precisely, when x^{q*} is the optimal solution vector for the single objective optimization of the q^{th} objective function f_q , the utopia point F^U is defined as follows:

$$F^U = [f_1(x^{1*}), f_2(x^{2*}), \dots, f_Q(x^{Q*})]. \quad (3.16)$$

The Utopia point F^U provides the lower bounds of the Pareto optimal set. Normally, the Utopia point is not feasible because of the conflicting nature of the individual objectives. The Nadir point is defined as:

$$F^N = [f_1^N, f_2^N, \dots, f_Q^N], \quad (3.17)$$

where each component f_q^N , $q = 1, \dots, Q$, is determined by

$$f_q^N = \max[f_q(x^{1*}), f_q(x^{2*}), \dots, f_q(x^{Q*})]. \quad (3.18)$$

the Nadir point F^N provides the upper bounds of the Pareto optimal set.

Considering the third normalization scheme that uses the differences of optimal function values in the Nadir and Utopia points, the normalization factors μ_q , $q = 1, \dots, Q$, are thus computed as follows:

$$\mu_q = \frac{1}{F_q^N - F_q^U}. \quad (3.19)$$

The aforementioned explanation on the computation of Nadir and Utopia points is taken from [52]. It is reproduced here for clarity.

In order to compute the normalization ranges $F_q^N - F_q^U$, it is necessary to solve Q optimization problems of the form $\min_x \{f_q(x) : x \in \Omega\}$ to obtain x^{q*} values. In practice, it may be computationally expensive to solve Q optimization problems especially if the problem dimensions are large. On the other hand, it is evident that exact solutions to the individual optimization problems are not required. One can come up with acceptable normalization factors if the estimates of the Utopia and Nadir points are known [52].

3.4.3.2 Normalization factor in the Weighted-Sum-Power-Delay-Min problem

After providing the method of computing the Nadir and Utopia points for a general example, we consider hereafter the case of the Weighted-Sum-Power-Delay-Min problem. Let C_p^U and C_d^U be the coordinates of the Utopia point, and let C_p^N and C_d^N be the coordinates of the Nadir Point. Therefore, the normalization factor β' is computed as follows:

$$\beta' = \frac{C_p^N - C_p^U}{C_d^N - C_d^U}. \quad (3.20)$$

To obtain the Utopia point, we solve two minimization problems presented in what follows.

3.4.3.2.1 Power Minimization The Power Minimization problem, denoted by Power-Min, consists in minimizing the total network power while ensuring the coverage constraint for all the network UEs. We introduce a new parameter $\rho_{i,j,k}$ that indicates whether user k is covered by BS i transmitting at power level j . Thus, Power-Min problem is given by:

$$\underset{\Lambda}{\text{minimize}} \quad C_p(\Lambda), \quad (3.21)$$

$$\text{subject to:} \quad \sum_{j \in J} \lambda_{i,j} = 1, \quad \forall i \in I, \quad (3.22)$$

$$\begin{aligned} \sum_{i \in I, j \in J} \rho_{i,j,k} \lambda_{i,j} &\geq 1, \quad \forall k \in K, \\ \lambda_{i,j} &\in \{0, 1\}, \quad \forall i \in I, \forall j \in J. \end{aligned} \quad (3.23)$$

Constraints (3.22) state that every BS transmits only at one power level. Constraints (3.23) ensure that a given UE is covered by at least one BS. Solving Power-Min problem provides the optimal operation mode of the network BSs denoted by Λ^{p*} , and C_p^U is thus equal to $C_p(\Lambda^{p*})$.

3.4.3.2.2 Delay Minimization The Delay Minimization problem, denoted by Delay-Min, consists in minimizing the total network delay. The delay is a function of Λ and Θ as shown in (3.9). Thus, to solve the problem, we assume that all BSs transmit at the highest power level and we denote by Λ^{d*} the matrix defining the operation mode of the BS. Therefore, the Delay-Min problem

is given by:

$$\begin{aligned} & \underset{\Theta}{\text{minimize}} && C_d(\Lambda^{d*}, \Theta), \\ & \text{subject to:} && (3.2), (3.3), (3.5), (3.6) \text{ and } (3.7). \end{aligned} \quad (3.24)$$

Solving Power-Min provides the optimal user association Θ^{d*} , and C_d^U is thus equal to $C_d(\Lambda^{d*}, \Theta^{d*})$.

The coordinates of the Nadir Point are computed as follows:

- $C_p^N = C_p(\Lambda^{d*})$, where Λ^{d*} is the matrix defining the operation mode of the BS when all BS transmit at the highest power level.
- $C_d^N = C_d(\Lambda^{p*}, \Theta^{p*})$, where Λ^{p*} is the optimal solution of Power-Min problem and Θ^{p*} is computed in such a way UEs are associated with the BS delivering the highest SNR.

3.5 Conclusion

In this chapter, we considered the joint Power-Delay minimization problem in green wireless access networks. We presented the multi-objective formulation of the problem and then explored two typical methods for solving multi-objective optimization problem, namely, the ϵ -constraints method and the weighted sum method. Moreover, we discussed the major challenges faced after resorting to a single-objective optimization problem. In particular, we focused on techniques for the normalization of objective functions in the weighted sum method. In the next chapters, we will provide a thorough study on the power-delay tradeoffs in two different wireless networks: IEEE 802.11 WLANs and cellular networks with LTE.

Part I

Joint Minimization of Power and Delay in WLANs

**Minimization of Power and
Delay in WLANs****4.1 Introduction**

In this chapter, we tackle the problem of joint power-delay minimization in green WLANs. We consider possible power saving by reducing the number of active BSs and adjusting the transmit power of those that remain active while minimizing the UE transmission delays. We consider the power consumption of an IEEE 802.11 WLAN, with access points working in infrastructure mode. We provide a realistic delay model used in WLANs, which is a unique feature of our work. As mentioned in the previous chapter, we resort to the weighted sum method in order to study the tradeoffs between minimizing the power consumption of the network and minimizing the sum of UE transmission delays in the network. Starting from a binary non-linear formulation of the problem, we formulate the Power-Delay minimization problem as a Mixed Integer Linear Programming (MILP) problem. Moreover, we introduce reference models for BS operation modes and user association that enable to assess the power saving and the delay obtained by the optimal solution. We provide extensive simulations for various decision preferences such as power minimization, delay minimization, and joint minimization of power and delay. Finally, we assess the computational complexity of the optimal solution.

The rest of the chapter is organized as follows. In Section 4.2, we describe the network model considering an IEEE 802.11 WLAN. In Section 4.3, we present the scalar optimization problem for WLANs. In Section 4.4, we transform the non-linear power-delay minimization problem into a MILP problem. In section 4.5, we present the reference models. We then provide extensive simulation results in Section 4.6. Finally, conclusions are given in Section 3.5.

4.2 Network Model

4.2.1 Assumptions

As the current downlink traffic on mobile networks is still several orders higher than the uplink traffic, we only consider the downlink traffic [53]. Moreover, we consider elastic traffic since it currently constitutes the majority of Internet traffic [54, 55]. Elastic traffic is generated by traditional data application such as file and mail download, web (*e.g.*, Twitter, Facebook), etc. This type of applications adapts their rate to available resource by means of a transport protocol like TCP. In fact, considering various traffic types can also be modeled in our approach. How to take into account both elastic and streaming traffic in our approach is explained in Chapter 8. Furthermore, we assume that:

- The network is in a static state where users are stationary. In other words, we take a snapshot of a dynamic system and optimize its current state.
- The network is in a saturation state. A saturation state is a worst-case scenario where every BS has persistent traffic toward UEs.

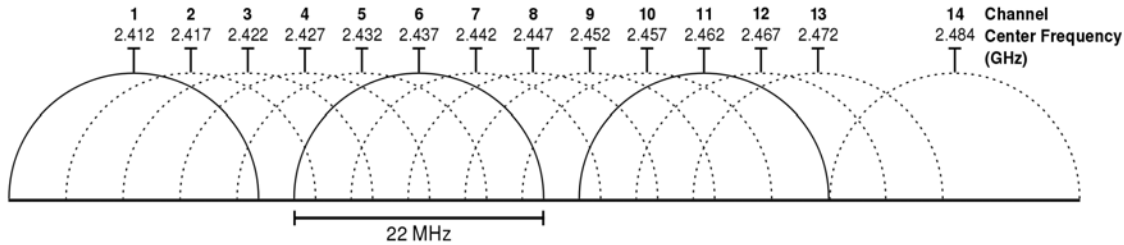


Figure 4.1: IEEE 802.11 channels in the 2.4 GHz band

The inter-cell interference is mitigated by assigning adjacent WLAN BSs¹ to the different IEEE 802.11 channels [56]. Particularly, in IEEE 802.11, the 2.4 GHz band consists of 14 overlapping channels, each occupying a bandwidth of 22 MHz, as shown in Fig. 4.1. The three non-overlapping channels (channels 1, 6, and 11) are commonly used when designing a WLAN. Thus, one can assign one of these three frequencies to each network BS in a way that minimizes co-channel overlap. Assignment of frequencies is essentially a map coloring problem with three colors [57].

1. For the case of WLANs, we use the term BS in this paper to designate an access point.

4.2.2 Data Rate and delay models in WLANs

We consider a fair-rate sharing scheme because it is the resource sharing model that stems from the Carrier Sense Multiple Access (CSMA) protocol adopted in WLANs. In fact, neglecting the uplink traffic leads to a fair access scheme on the downlink channel. Accordingly, when a low-rate UE captures the channel, this UE will penalize the high-rate UEs. This also reduces the fair access strategy to a case of fair rate sharing of the radio channel among UEs [30] with the assumption of neglecting the 802.11 waiting times (*i.e.*, DIFS², SIFS³). Thus, all UEs will have the same mean throughput. When UE k is associated with BS i transmitting at level j , its mean throughput $R_{i,j,k}^W$ depends on its peak rate $\chi_{i,j,k}$ and the peak rates of other UEs associated with this same BS ($\chi_{i,j,k'}, k' \neq k$). $R_{i,j,k}^W$ is given by [22, 23]:

$$R_{i,j,k}^W = \frac{1}{\frac{1}{\chi_{i,j,k}} + \sum_{k'=1, k' \neq k}^{N_u} \frac{\theta_{i,k'}}{\chi_{i,j,k'}}}, \quad (4.1)$$

where $\theta_{i,k'}$ is the binary variable indicating whether or not UE k' is associated with BS i . Let $T_{i,j,k}^W$ denote the transmission delay of UE k from BS i transmitting at level j in the case of a WLAN. The transmission delay for a given UE, defined as the inverse of the throughput perceived by this UE (cf. Section 3.2), is given by:

$$T_{i,j,k}^W = \frac{1}{\chi_{i,j,k}} + \sum_{k'=1, k' \neq k}^{N_u} \frac{\theta_{i,k'}}{\chi_{i,j,k'}}. \quad (4.2)$$

4.2.3 Power Consumption Model in WLANs

We consider the power consumption of an IEEE 802.11 WLAN, with BSs working in infrastructure mode. In practice, the transmission power of a WLAN BS is discrete and the maximum number of transmit power levels is equal to 5 or 6 depending on the BS manufacturer [58]. Following the model proposed in [26], the power consumption of a WLAN BS is modeled as a linear function of the average transmit power:

$$p_{i,j}^W = L(a\pi_j^W + b), \quad (4.3)$$

where $p_{i,j}^W$ and π_j^W denote the average consumed power per WLAN BS i and the transmit power at level j respectively. The coefficient a accounts for the power consumption that scales with the transmit power due to radio frequency amplifier and feeder losses. The coefficient b models the power consumed independently of the transmit power due to signal processing, power supply

2. DIFS: Distributed Coordination Function Interframe Space

3. SIFS: Short Interframe Space

consumption and cooling. For $j = 1$, we consider that the BS transmits at the highest power level, and for $j = N_L$, the BS is in sleep mode. L reflects the activity level of the WLAN BSs. Since we assume that the network is in a saturation state, L is equal to one; for instance, each active WLAN BS has at least one UE requesting data and to which all resources are being allocated [10, 26].

4.3 Power-Delay Minimization Problem in WLANs

In order to study the tradeoffs between minimizing the power consumption of the network and minimizing the sum of UE transmission delays in the network, we resort to the weighted sum method as explained in Section 3.4.2 in the previous chapter. Let Weighted-Sum-Power-Delay-Min-WLAN denote the scalar optimization problem for WLANs. Let C_p^W , C_d^W and C_t^W denote the total network power, the total network delay and the total network cost for this case, respectively. C_p^W and C_d^W are obtained from (3.8) and (3.9) by replacing $p_{i,j}$ and $T_{i,j,k}$ by the expressions of $p_{i,j}^W$ and $T_{i,j,k}^W$, respectively. Therefore,

$$C_p^W(\Lambda) = \sum_{i \in I, j \in J} p_{i,j}^W \lambda_{i,j} = \sum_{i \in I, j \in J} (a\pi_j^W + b) \lambda_{i,j}, \quad (4.4)$$

$$C_d^W(\Lambda, \Theta) = \sum_{i \in I, j \in J, k \in K} T_{i,j,k}^W \lambda_{i,j} \theta_{i,k} = \sum_{i \in I, j \in J, k \in K} \left(\frac{\lambda_{i,j} \theta_{i,k}}{\chi_{i,j,k}} + \sum_{k'=1, k' \neq k}^{N_u} \frac{\lambda_{i,j} \theta_{i,k} \theta_{i,k'}}{\chi_{i,j,k'}} \right), \quad (4.5)$$

$$C_t^W(\Lambda, \Theta) = \alpha C_p^W(\Lambda) + \beta \beta' C_d^W(\Lambda, \Theta). \quad (4.6)$$

The Weighted-Sum-Power-Delay-Min-WLAN problem consists of finding an optimal set of active BSs transmitting at a specific power level and an optimal user association that minimize the total network cost C_t^W . Consequently, the Weighted-Sum-Power-Delay-Min-WLAN problem is

given by:

$$\begin{aligned} \underset{\Lambda, \Theta}{\text{minimize}} \quad & C_t^W(\Lambda, \Theta) = \alpha \sum_{i \in I, j \in J} (a\pi_j^W + b)\lambda_{i,j} \\ & + \beta\beta' \sum_{i \in I, j \in J, k \in K} \left(\frac{\lambda_{i,j}\theta_{i,k}}{\chi_{i,j,k}} + \sum_{k'=1, k' \neq k}^{N_u} \frac{\lambda_{i,j}\theta_{i,k}\theta_{i,k'}}{\chi_{i,j,k'}} \right), \end{aligned} \quad (4.7)$$

$$\text{subject to: } \sum_{j \in J} \lambda_{i,j} = 1, \quad \forall i \in I, \quad (4.8)$$

$$\sum_{i \in I} \theta_{i,k} = 1, \quad \forall k \in K, \quad (4.9)$$

$$\lambda_{i,j} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J, \quad (4.10)$$

$$\theta_{i,k} \in \{0, 1\}, \quad \forall i \in I, \forall k \in K, \quad (4.11)$$

$$\theta_{i,k} = 0, \quad \forall i \in I, \forall k \in K / \chi_{i,1,k} \leq \chi_{th}, \quad (4.12)$$

$$\lambda_{i,N_l}\theta_{i,k} = 0, \quad \forall i \in I, \forall k \in K, \quad (4.13)$$

$$\lambda_{i,j}\theta_{i,k} = 0, \quad \forall i \in I, \forall j \in \{2, \dots, N_l - 1\}, \forall k \in K / \chi_{i,j,k} \leq \chi_{th}. \quad (4.14)$$

4.3.1 Optimal Solution

The *Weighted-Sum-Power-Delay-Min-WLAN* problem is a binary non-linear optimization that consists in minimizing the objective function (4.7) subject to the constraints (4.8) - (4.11). In our work [59], we resort to an exhaustive search algorithm to compute the optimal solution of the problem. The exhaustive search algorithm explores all the possible solutions to compute the minimum of the objective function. We note that the time complexity of this exhaustive search algorithm is function of the number of users, the number of BSs and the corresponding number of transmit power levels. Precisely, the objective function should be evaluated for each value of $\theta_{i,k}$ and $\lambda_{i,j}$. As $\theta_{i,k} = 0$ or 1 for each $i = 1, \dots, N_{bs}$ and $k = 1, \dots, N_u$, then the cardinality of the set of values corresponding to $\theta_{i,k}$ is $2^{N_{bs} \cdot N_u}$. Similarly, for $\lambda_{i,j}$, the cardinality of the set of values corresponding to $\lambda_{i,j}$ is $2^{N_{bs} \cdot N_l}$. Hence the time complexity for computing the minimum value of the objective function over these sets is in $\mathcal{O}(2^{N_{bs} \cdot N_u} \cdot 2^{N_{bs} \cdot N_l}) = \mathcal{O}(2^{N_{bs} \cdot (N_u + N_l)})$. Thus, the exhaustive search is computationally intensive, and rapidly becomes intractable for small sized networks. Therefore, in our work [60], we propose to convert the *Weighted-Sum-Power-Delay-Min-WLAN* problem into a MILP problem in order to compute its optimal solution. In the following, we provide the MILP formulation of the problem.

4.4 MILP Formulation of the Power-Delay Minimization in WLANs

A MILP problem consists of a linear objective function, a set of linear equality and inequality constraints and a set of variables with integer restrictions. The number of constraints and variables are important factors when estimating if a problem is tractable. Generally, MILP problems are solved using a linear-programming based on the branch-and-bound approach. The idea of this approach is to solve the Linear Program (LP) relaxations of the MILP and to look for an integer solution by branching and bounding on the decision variables provided by the LP relaxations. Thus, in a branch-and-bound approach, the number of integer variables determines the size of the search tree and influences the running time of the algorithm.

4.4.1 Problem Formulation

To linearize the non-linear optimization Weighted-Sum-Power-Delay-Min-WLAN problem, we replace the non-linear terms by new variables and additional inequality constraints. These latter ensure that the new variables behave according to the non-linear terms they are replacing. Particularly, we replace each quadratic term $\lambda_{i,j}\theta_{i,k}$ in the objective function (4.7) and in the constraints (4.13) and (4.14) by a new linear variable $y_{i,j,k}$ and add the following three inequalities to the set of constraints:

$$y_{i,j,k} - \lambda_{i,j} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k \in K, \quad (4.15)$$

$$y_{i,j,k} - \theta_{i,k} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k \in K, \quad (4.16)$$

$$\lambda_{i,j} + \theta_{i,k} - y_{i,j,k} \leq 1, \quad \forall i \in I, \forall j \in J, \forall k \in K. \quad (4.17)$$

The inequalities (4.15) and (4.16) ensure that $y_{i,j,k}$ equals zero when either $\lambda_{i,j}$ or $\theta_{i,k}$ equals zero, while the inequalities (4.17) force $y_{i,j,k}$ to be equal to one if both $\lambda_{i,j}$ and $\theta_{i,k}$ equal one. Moreover, the constraints (4.13) and (4.14) will be replaced by the constraints (4.18) and (4.19), respectively:

$$y_{i,N_l,k} = 0, \quad \forall i \in I, \forall k \in K, \quad (4.18)$$

$$y_{i,j,k} = 0, \quad \forall i \in I, \forall j \in \{2, \dots, N_l - 1\}, \forall k \in K / \chi_{i,j,k} \leq \chi_{th}. \quad (4.19)$$

Similarly, we replace each term $\lambda_{i,j}\theta_{i,k}\theta_{i,k'}$ in the objective function (4.7) by a new variable $z_{i,j,k,k'}$ and add the following inequalities to the set of constraints:

$$z_{i,j,k,k'} - \lambda_{i,j} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (4.20)$$

$$z_{i,j,k,k'} - \theta_{i,k} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (4.21)$$

$$z_{i,j,k,k'} - \theta_{i,k'} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (4.22)$$

$$\lambda_{i,j} + \theta_{i,k} + \theta_{i,k'} - z_{i,j,k,k'} \leq 2, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (4.23)$$

$$z_{i,j,k,k'} - z_{i,j,k',k} = 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K. \quad (4.24)$$

The inequalities (4.20), (4.21) and (4.22) ensure that $z_{i,j,k,k'}$ is equal to zero when either $\lambda_{i,j}$ or $\theta_{i,k}$ or $\theta_{i,k'}$ equals zero, while the inequalities (4.23) force $y_{i,j,k}$ to be equal to one if $\lambda_{i,j}$, $\theta_{i,k}$ and $\theta_{i,k'}$ are equal to one. Furthermore, as $\lambda_{i,j}\theta_{i,k}\theta_{i,k'} = \lambda_{i,j}\theta_{i,k'}\theta_{i,k}$, constraints (4.24) force $z_{i,j,k,k'}$ to be equal to $z_{i,j,k',k}$. In addition, we give the bound constraints for the variables $y_{i,j,k}$ and $z_{i,j,k,k'}$ as follows:

$$0 \leq y_{i,j,k} \leq 1, \quad \forall i \in I, \forall j \in J, \forall k \in K, \quad (4.25)$$

$$0 \leq z_{i,j,k,k'} \leq 1, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K. \quad (4.26)$$

Finally, the MILP Weighted-Sum-Power-Delay-Min-WLAN problem is given by:

$$\begin{aligned} \underset{\Lambda, Y, Z}{\text{minimize}} \quad & C_t^W(\Lambda, Y, Z) = \alpha \sum_{i \in I, j \in J} (a\pi_j^W + b)\lambda_{i,j} \\ & + \beta\beta' \sum_{i \in I, j \in J, k \in K} \left(\frac{y_{i,j,k}}{\chi_{i,j,k}} + \sum_{k' \in K, k' \neq k} \frac{z_{i,j,k,k'}}{\chi_{i,j,k'}} \right), \\ \text{subject to:} \quad & (4.8) \text{ to } (4.12) \text{ and } (4.15) \text{ to } (4.26); \end{aligned} \quad (4.27)$$

where $y_{i,j,k}$ and $z_{i,j,k,k'}$ are respectively the elements of the matrices Y and Z . The main notations used in this chapter are reported in Tab. 4.1.

4.5 BS Operation mode and User Association Reference Models

In legacy WLANs or cellular networks, BSs transmit at a fixed power level and UEs are associated with the BS delivering the highest SNR [61, 27]. Based on these legacy networks, we devise a reference model composed of: *i*) the Highest Power Level (HPL) as the reference model for BS operation mode, which assumes that all BSs transmit at the highest power level; *ii*) the Power Based User Association (Po-UA) as the reference user association model, which associates a UE with the BS where it obtains the highest SNR. In what follows, we denote the reference model by Po-UA/HPL. The total network power and the total network delay of this model will serve as reference values for comparison of the results.

Table 4.1: Notation Summary

Notation	Definition
I	Set of network BSs
J	Set of transmit power levels of a given BS
K	Set of UEs in the network
N_{bs}	The total number of BSs
N_l	The total number of transmit power levels
N_u	The total number of UEs
$p_{i,j}$	The average consumed power per BS i transmitting at power level j
π_j^W	The transmit power at level j for WLAN BSs
$\chi_{i,j,k}$	The peak rate perceived by UE k from BS i transmitting at level j
$T_{i,j,k}^W$	The transmission delay of UE k associated with WLAN BS i transmitting at level j
$\theta_{i,k}$	A binary variable that indicates if UE k is associated with BS i
$\lambda_{i,j}$	A binary variable that indicates if BS i transmits at power level j
$y_{i,j,k}$	A binary variable that indicates if UE k is associated with BS i transmitting at power level j
$z_{i,j,k,k'}$	A binary variable that indicates if UE k and UE k' are associated with BS i transmitting at power level j

4.6 Performance Evaluation in WLANs

4.6.1 Evaluation Method

To study the tradeoff between minimizing the power consumption of the network and minimizing the sum of UE transmission delays in WLANs, we tune the values of the weights α and β (in (4.27)), associated with the total network power and total network delay respectively, and investigate the obtained solutions. We consider five settings illustrated in Tab. 4.2. Settings S1 and S2 match the case where preference is given to power saving. Setting S3 matches the case where the power and delay are equally important. Settings S4 and S5 match the case where preference is given to minimizing delay.

Moreover, the normalization factor β' is calculated in each simulation so as to scale the total network power and the total network delay as explained in Section 3.4.3.2 in Chapter 3. Furthermore, we adopt the Monte Carlo method by generating 50 snapshots with different random uniform UE distributions. After computing all the snapshots, we provide the 95% Confidence

Table 4.2: Five studied settings in WLANs.

Settings	Weighting coefficients value	Description
S1	$\alpha = 0.99, \beta = 0.01$	Preference is given to saving power
S2	$\alpha = 0.75, \beta = 0.25$	
S3	$\alpha = 0.5, \beta = 0.5$	Balance the tradeoff between minimizing power and delay
S4	$\alpha = 0.25, \beta = 0.75$	Preference is given to minimizing delay
S5	$\alpha = 0.01, \beta = 0.99$	

Interval (CI) for each simulation result.

Furthermore, we compute the optimal solution of our MILP Weighted-Sum-Power-Delay-Min-WLAN problem with the GLPK (GNU Linear Programming Kit) solver [62] over a network topology composed of nine cells ($N_{bs} = 9$) using the IEEE 802.11g technology and six users in each cell ($N_u = 9 \times 6 = 54$). The positioning of the WLAN BSs in the network is performed following a grid structure and the positioning of users is generated randomly following a uniform distribution. Moreover, we assign adjacent BSs to different IEEE 802.11 channels to mitigate the inter-cell interference.

In the BS power model, for simplicity, we set the number of transmit power levels to three ($N_l = 3$). Precisely, an active BS is able to transmit at two different power levels, and when the power level equals three, the BS is in sleep mode. In fact, we consider that in sleep mode, the BS consumes only power due to signal processing neglecting the cooling. It is estimated that the power consumption of signal processing circuits accounts for only 10% of the total consumed power [63]. Therefore, we assume that in sleep mode, the WLAN BS power consumption is negligible. Moreover, we aim to compute the optimal solution of the MILP problem. Thus, if we increase N_l , the granularity will be finer but the problem becomes intractable. The input parameters of the power consumption model in (4.3) are:

- as proposed in [26], $a = 3.2$ and $b = 10.2$;
- as proposed in [58], the transmit power at level one and two are $\pi_1^W = 0.03$ W and $\pi_2^W = 0.015$ W, respectively.

Hence, the average power consumed per BS $i \in I$ at the first, second, and third power levels are given by $p_{i,1} = 10.296$ W, $p_{i,2} = 10.248$ W, and $p_{i,3} = 0$, respectively.

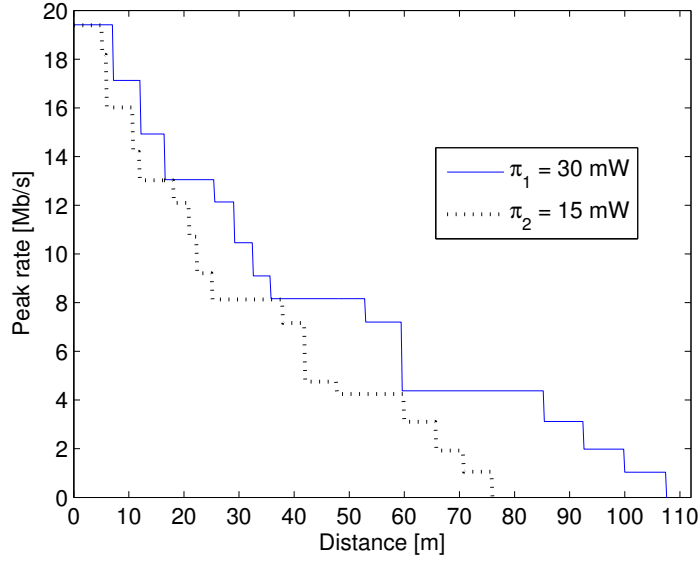


Figure 4.2: Peak rates in IEEE 802.11g for different transmit power levels.

4.6.1.1 Peak rate and coverage area computation

Rather than considering the physical peak rate provided by the IEEE 802.11g standard [25], we compute the application layer peak rate perceived by the UE. In particular, we implement in NS2 [64], a benchmark scenario that enables the computation of the peak rate perceived by the UE from the serving BS and the coverage area of the WLAN BS. The benchmark scenario consists of a free propagation model to characterize the WLAN radio environment, an IEEE 802.11g BS using the 2.4 GHz frequency band, and a single UE at different positions. This UE receives Constant Bit Rate (CBR) traffic from the BS with a packet size of 1000 bytes and an inter-arrival time of 0.4 ms corresponding to a rate of 20 Mbit/s. This leads to a saturation state of the network according to the assumption presented in Section 4.2.1. In these conditions, the throughput experienced by the single UE is the maximum achievable throughput (peak rate). We run this scenario for each BS transmit power level ($\pi_1 = 0.03$ W and $\pi_2 = 0.015$ W) to obtain $\chi_{i,1,k}$ and $\chi_{i,2,k}$ for the UE, respectively. Figure 4.2 shows the peak rate perceived by the UE from the BS, transmitting at the first and the second power level, as a function of the distance. In addition, the coverage radius for the first and second power levels are $R_1 = 107.4$ m and $R_2 = 75.8$ m, respectively. These radii correspond to a cell edge peak rate that equals 1 Mb/s ($\chi_{th} = 1$ Mb/s) on the downlink. This peak rate is the minimum value to be maintained in order to consider that a given user is covered by a BS. It corresponds to an SNR threshold that equals -0.5 dB at the cell boundary.

In the following, the simulation results are plotted as a function of the inter-cell distance D . For small inter-cell distances, we obtain a dense coverage area, while large inter-cell distances

Table 4.3: Covering BSs per UE vs. inter-cell distance in WLAN scenarios.

Inter-cell distance [m]	120.8	134.2	147.6	161.1	174.5	187.9	201.3	214.8
Number of covering BSs per UE	2.02	1.76	1.53	1.38	1.25	1.15	1.05	1.00

produce a sparse coverage area. Table 4.3 shows the average number of covering BSs per UE as a function of the inter-cell distance. For $D = 120.8$ m, we obtain a dense coverage area where the average number of covering BSs per UE is 2.02. As D increases, the average number of covering BSs per UE decreases to reach one when there is no overlap between cells ($D = 2R_1$). Figure 4.3 shows an example of the network topology with an inter-cell distance equals 120.8 m.

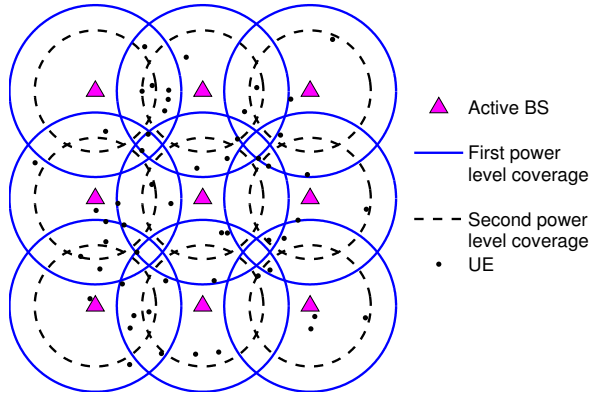


Figure 4.3: An example of the WLAN topology with $N_{bs} = 9$, $N_l = 3$, $N_u = 54$ and an inter-cell distance $D = 120.8$ m.

4.6.2 Simulation Results

Let us start by examining the power saving achieved for the five considered settings, which is computed as follows:

$$100 \times \left(1 - \frac{\text{total network power for the considered setting}}{\text{total network power for Po-UA/HPL model}}\right), \quad (4.28)$$

where the total network power is computed according to the value of C_p^W in (4.4). Recall that in the Po-UA/HPL reference model, all BSs transmit at the highest power level.

Figure 4.4 plots the percentage of power saving for the five considered settings as a function of the inter-cell distance D . S1 and S2 have the highest percentage of power saving, followed successively by S3 then S4 for D ranging from 120.8 m to 161.1 m, while no power saving is obtained for $D \geq 161.1$ m. For instance, when $D = 120.8$ m, we obtain power saving of up to

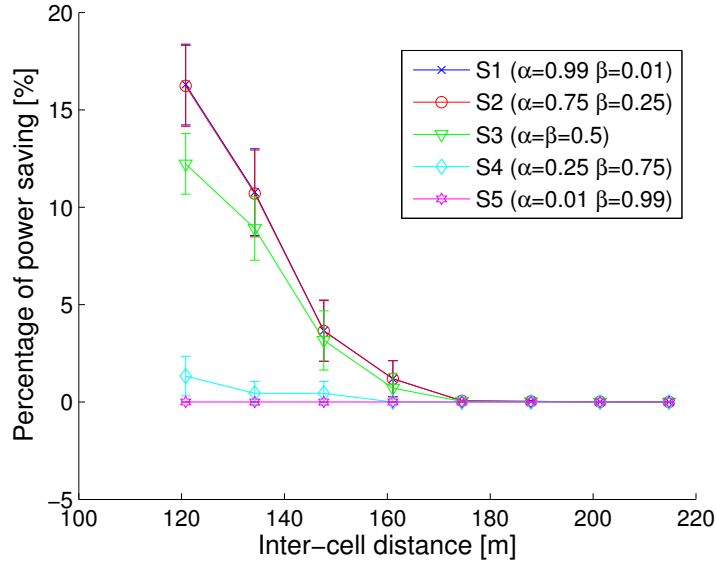


Figure 4.4: Power saving for the considered settings in WLANs.

16% in S1 and S2, followed by S3 at 12.22% and by S4 at 1.33%. S5 has no power saving for any distance. In other words, in S5, we obtain a BS operation mode where all BSs transmit at the highest power level (similar to the Po-UA/HPL model). Precisely, in this setting preference is given to minimizing the sum of UE transmission delays, so when all BSs transmit at the highest level, UEs experience lower delays in comparison with the case where some of the BSs transmit at the second power level or are switched off.

In order to examine the reason behind significant power savings in settings S1, S2 and S3, we plot in Fig. 4.5, the percentage of the BS operation modes for D ranging from 120.8 m to 161.1 m. We notice that S1 has the highest percentages of BSs transmitting at the second power level and switched-off, followed by S2 then by S3 for the different values of D . Moreover, for these three settings, we note that when D increases, the percentage of switched-off BSs decreases, and the percentage of BSs transmitting at the second power level increases. On the one hand, this explains the decreasing curves for the corresponding inter-cell distances in Fig. 4.4. On the other hand, for low values of D (*i.e.*, 120.8 m), this behavior is due to the relatively high number of covering BSs per UE (*i.e.*, 2.02 as shown in Tab. 4.3). Thus, the possibility of switching off the BS or transmitting at a low power level is high. However, for large values of D , the number of covering BSs per UE decreases, and thus the possibility to switch off a BS or to transmit at low power level decreases due to the coverage constraints.

We now investigate the total network delay for the considered settings compared to the Po-UA/HPL model while varying the inter-cell distance D . The total network delay is computed

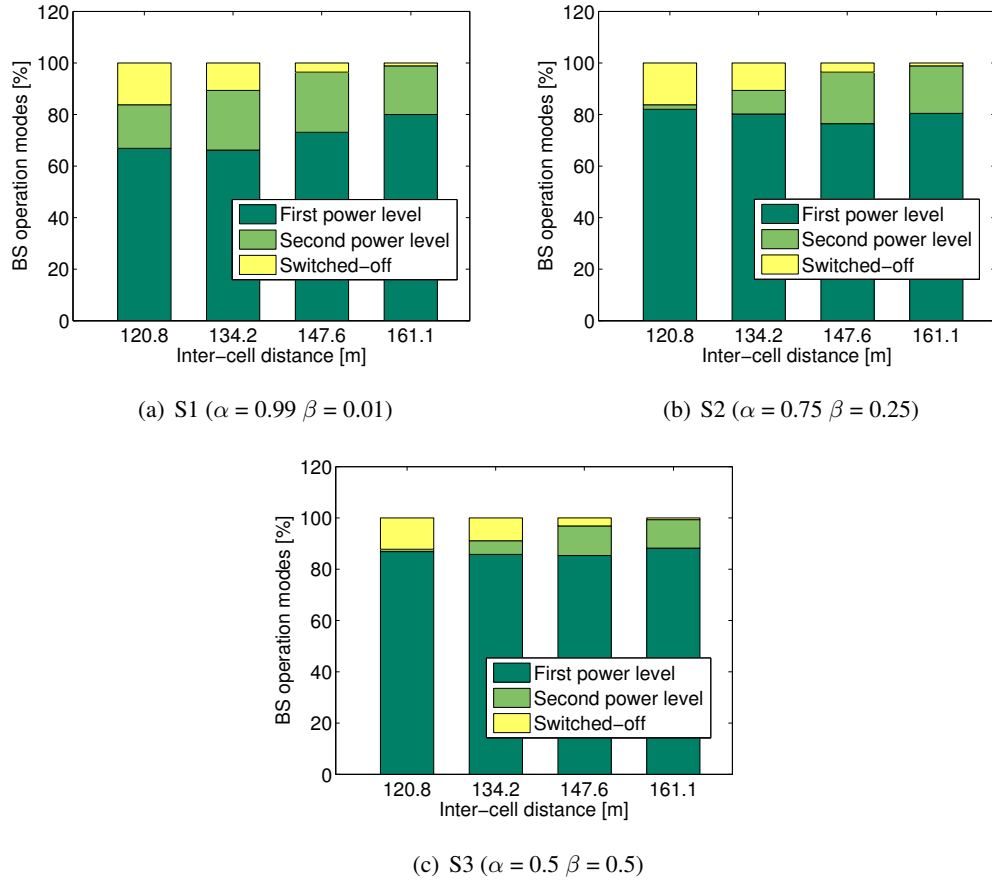


Figure 4.5: Percentage of BS operation modes in settings S1, S2 and S3 in WLANs.

according to the value of C_d^W in (4.5). For the comparison of the five settings, Fig. 4.6 shows that S5 has the lowest total network delay, followed successively by S4, S3, S2, and finally S1. Particularly, in S5, more weight is given to minimizing the delay ($\beta = 0.99$), thus we obtain a network operation mode where all BSs transmit at the highest power level (as shown in Fig. 4.4). The problem becomes a user association problem that aims to minimize the sum of network UE transmission delays. With the decrease of β , more BSs are switched off or transmit at the second power level (as shown in Fig. 4.5), and thereby UEs will experience higher delay. Compared to the Po-UA/HPL model, we obtain a delay reduction for all the inter-cell distances in S4 and S5. For instance, the delay reduction is 4.5% and 6.64% in S4 and S5, respectively, for $D = 120.8$ m. However, we obtain a higher total network delay compared to Po-UA/HPL for all values of D in S1, S2 and S3. Further, we see that in S4 and S5, the total network delay has an increasing curve. Precisely, for a given UE distribution, when D increases, the SNR of the UE will decrease, causing the delay to increase. Similarly, we see that in S2 and S3, the total network delay has an increasing curve but with a lower slope at the first inter-cell distances. In S1, the total network delay has a decreasing curve for D between 120.8 m and 161.1 m and then it increases for $D \geq 161.1$ m. In

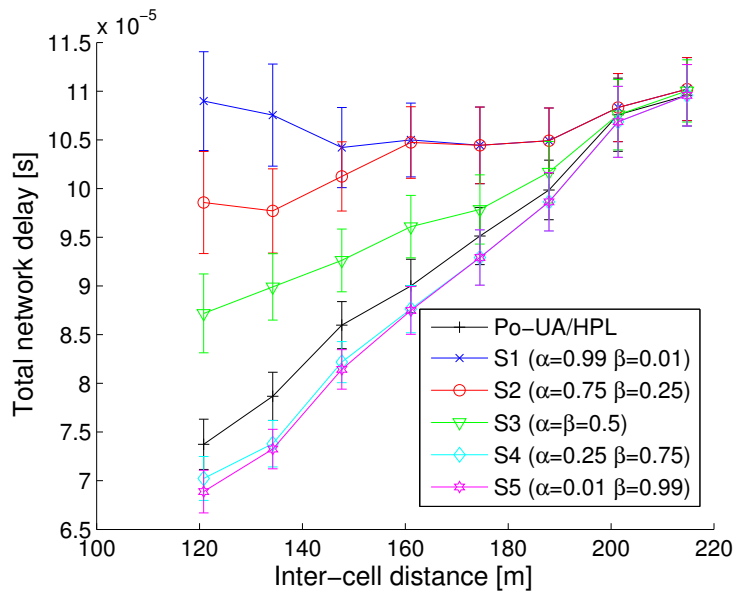


Figure 4.6: Total network delay for the considered settings and for Po-UA/HPL in WLANs.

particular, for D between 120.8 m and 161.1 m, more BSs transmit at either the highest power level or the second power level (as shown in Fig. 4.5(a)). UEs will thereby experience a lower delay. Note that all the curves converge to the same point. Indeed, when D increases, the cell overlap decreases, and thus, the optimal solution for the five settings turns on the BSs to achieve a point where all the BSs transmit at the highest power level. Therefore, the problem boils down to a user association that minimizes the sum of UE delays.

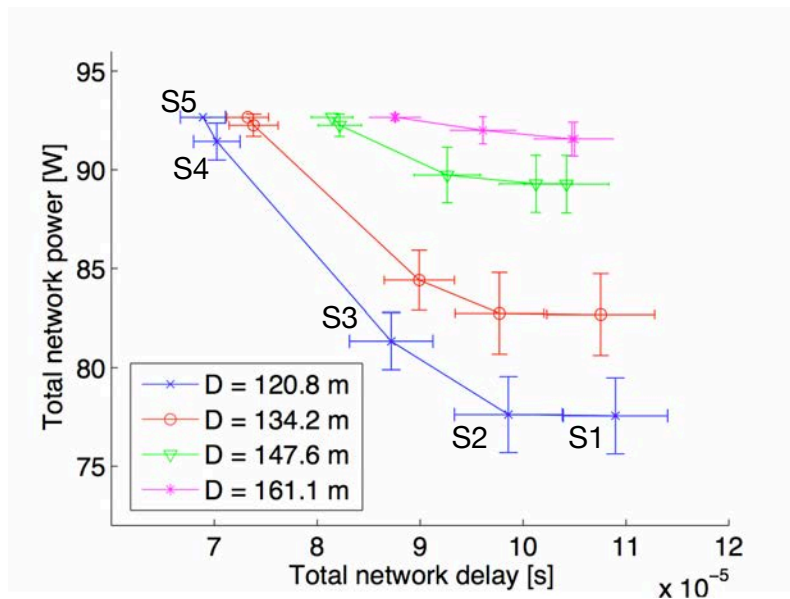


Figure 4.7: Pareto frontier at different inter cell distances in WLANs scenario.

In Fig. 4.7, we plot the power-delay tradeoff curves for different inter-cell distances D ranging from 120.8 m to 161.1 m. The five points of the illustrated curves are obtained by plotting the values of the 95% CI of the total network power as a function of the 95% CI of the total network delay for the five considered settings. For all the inter-cell distances, we obtain a reduction in the network power consumption at the cost of delay increase. In particular, for $D = 120.8$ m, in S5 ($\alpha = 0.01$, $\beta = 0.99$), we obtain the solution with the lowest total network delay (6.88×10^{-5} s) and the highest total network power (92.664 Watt); while in S1 ($\alpha = 0.99$, $\beta = 0.01$), we obtain the solution with the lowest total network power (77.62 W) and the highest total network delay (10.90×10^{-5} s). Moreover, we note that when D increases, the tradeoff curves become flat. For instance, for $D = 161.1$ m, we obtain similar total network power in the five settings. Indeed, for sparse coverage area, the problem in the five settings becomes similar to a user association problem where there is no longer a significant power-delay tradeoff. In fact, these curves represent the Pareto frontier at different inter-cell distances. Hence, a network operator has the option to choose the operation point of the network. For instance, the operator can choose the optimal inter-cell distance of his network, that achieves the desired power-delay tradeoff. Moreover, the operator has the choice to privilege power saving, minimize delay, or balance the tradeoff between the two objectives.

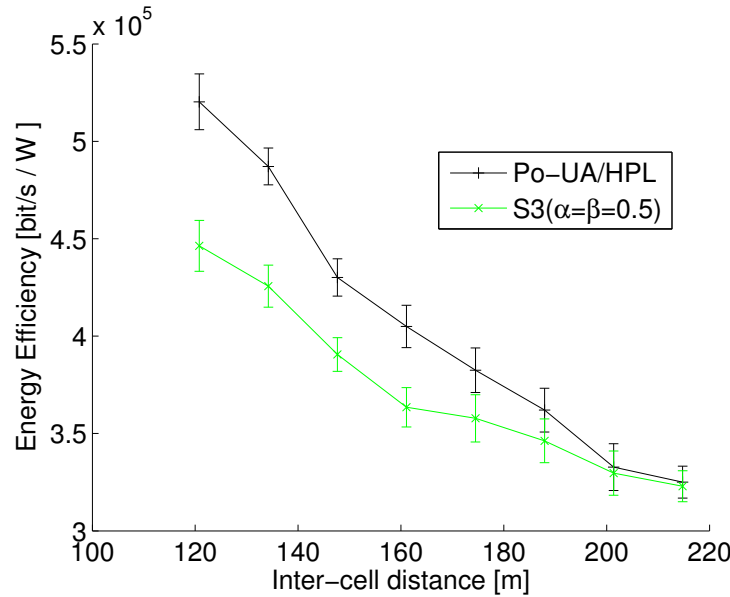


Figure 4.8: Energy efficiency for setting S3 and for Po-UA/HPL in WLANs.

We now assess the Energy Efficiency (EE) (cf. Section 2.1) for setting S3 ($\alpha = \beta = 0.5$) and for Po-UA/HPL, while varying the inter-cell distance D . The energy efficiency is defined as the mean throughput provided by the network over the power consumption of the network BSs. For

both setting S3 and Po-UA/HPL, the energy efficiency is computed as follows:

$$EE = \frac{\sum_{i \in I, j \in J, k \in K} R_{i,j,k}^W}{C_p^W}, \quad (4.29)$$

where $R_{i,j,k}^W$ is the mean throughput of UE k associated with BS i transmitting at power level j , computed according to (4.1). C_p^W is the total network power computed according to (4.4). Unexpectedly, Fig. 4.8 shows that the energy efficiency of Po-UA/HPL is higher than that of S3 for all the inter-cell distances. Precisely, in Po-UA/HPL, all BSs transmit at the highest power level. This increases the throughput of each UE in the network. Contrary to setting S3, 12% of the BSs are switched-off (as shown in Fig. 4.5(c)) causing UEs to experience lower throughput. This leads to an interesting conclusion that minimizing the power consumption while minimizing the transmission delay is not equivalent to maximizing the energy efficiency.

4.6.3 Computational complexity

The MILP Weighted-Sum-Power-Delay-Min-WLAN problem is solved using the branch-and-bound approach over the CPLEX solver. In this approach, the number of integer variables determines the size of the search tree and impacts the computation time of the algorithm. Thus, in order to assess the computational complexity of the optimal solution, we calculate in the following its computation time and the number of binary integer variables. Also, we compute the number of non-zero elements of the matrix defining the constraints of the minimization problem.

Figure 4.9 shows the 95% CI of the computational complexity measurements as a function of the inter-cell distance D . We note that the computation time of the optimal solution decreases when D increases as shown in Fig. 4.9(a). Precisely, when D increases, the number of binary integer variables and non-zero elements decreases as shown in Fig. 4.9(b) and Fig. 4.9(c). In fact, when the inter-cell distance increases, the number of UEs covered by each BS decreases. This reduces the related solution space (for selecting the BS transmit power level, and the user association). Moreover, we note that for $D = 120.8$ m, the computation time is relatively high (1091s) and for very dense networks (*e.g.*, $D \leq 120.8$ m), the problem becomes intractable.

4.7 Conclusion

In this chapter, we advocate a joint optimization for the problem of power saving and transmission delay minimization in green WLANs. Thus, we formulate a non-linear optimization problem that consists in finding a tradeoff between reducing the network power consumption and selecting the best user association that incurs the lowest sum of user transmission delays. We provide

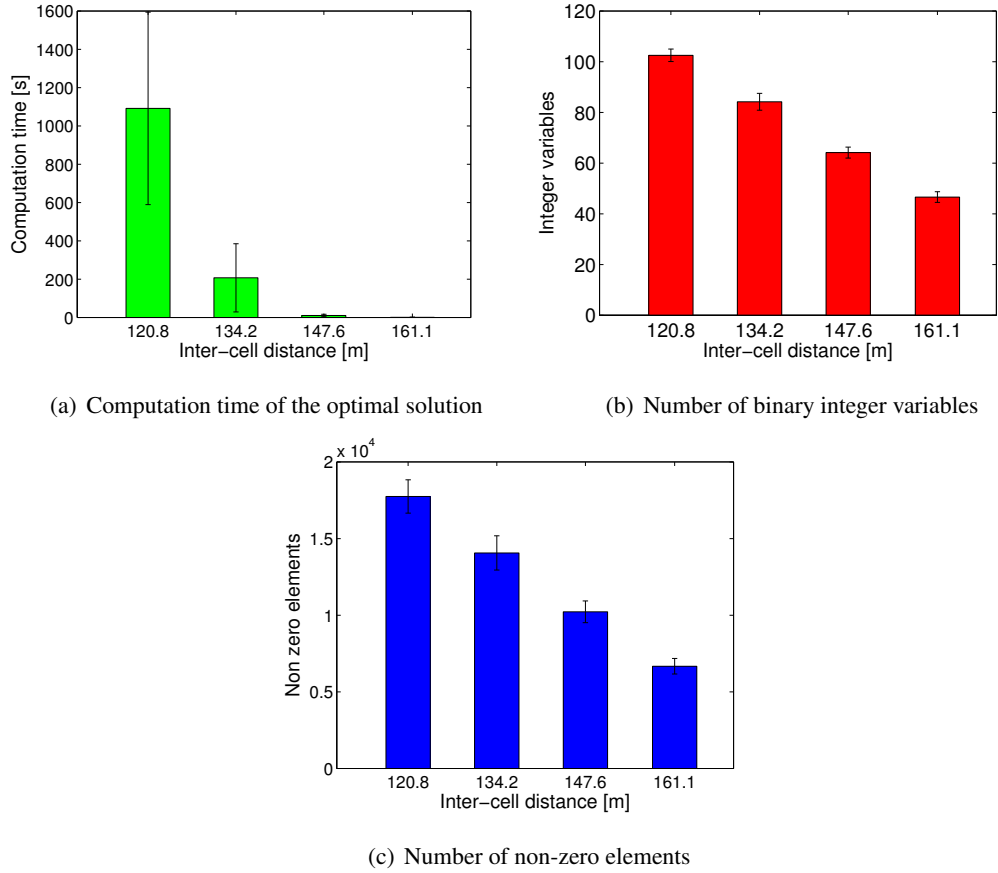


Figure 4.9: Optimal solution computational complexity measurements.

a MILP formulation of our problem that makes it computationally tractable. Different cases reflecting various decision preferences are studied by tuning the weights of the power and delay components of the network total cost. Simulation results validated that the network power is saved at the cost of an increase in network delay. Moreover, compared to the most frequently deployed WLANs where BSs transmit at a fixed transmit power level, results showed that for a power reduction setting, we obtain power savings of up to 16% whereas for a delay minimization setting, we obtain delay reduction delay of up to 6%. Our optimization results reveal the impact of the network topology, particularly the inter-cell distance, on both objectives. An interesting conclusion is driven from our analysis: minimizing the power consumption while minimizing the transmission delay does not lead to maximizing the network energy efficiency.

However, the MILP formulation cannot deliver solutions in a reasonable amount of time due to computational complexity issues. Therefore, in the next chapter, we propose a heuristic algorithm for the joint power-delay minimization problem that overcomes such issues, especially considering the dense deployment of BSs.

A Greedy Heuristic Algorithm for Joint Minimization of Power and Delay in WLANs

5.1 Introduction

Due to computational complexity issues, the MILP formulation of the power-delay minimization problem, introduced in Chapter 4, cannot deliver solutions in a reasonable amount of time. As a result, we propose here a greedy heuristic algorithm for the power-delay minimization problem in green WLANs [65]. The proposed heuristic aims to compute the transmit power level of the BSs deployed in the network and associate UEs with these BSs in a way that jointly minimizes the total network power and the total network delay. In order to evaluate the efficiency of the heuristic algorithm for the power-delay minimization problem, we compare the results obtained by this heuristic with the MILP optimal solution and existing solutions. Simulation results show that the proposed algorithm has a low computational complexity which makes it advantageous compared with the optimal scheme, particularly in dense networks.

The rest of the chapter is organized as follows. In Section 5.2, we present the power-delay minimization problem. In Section 5.3, we present our proposed greedy heuristic algorithm. In Section 5.4, we present the existing approaches. In Section 5.5, we provide the simulation results. Conclusions are given in Section 5.6.

5.2 Power-Delay Minimization Problem in WLANs

We introduced the power-delay minimization problem in green WLANs in the previous chapter. The considered problem consists of finding the optimal transmit power level of the BSs deployed in the network and optimal user association that minimize the total network cost. The total network cost is defined as the weighted sum of total network power and total network delay. The total network power is given by:

$$C_p^W(\Lambda) = \sum_{i \in I, j \in J} (a\pi_j^W + b)\lambda_{i,j}, \quad (5.1)$$

The total network delay is given by:

$$C_d^W(\Lambda, \Theta) = \sum_{i \in I, j \in J, k \in K} \left(\frac{\lambda_{i,j}\theta_{i,k}}{\chi_{i,j,k}} + \sum_{k'=1, k' \neq k}^{N_u} \frac{\lambda_{i,j}\theta_{i,k}\theta_{i,k'}}{\chi_{i,j,k'}} \right), \quad (5.2)$$

Consequently, the objective function of the Weighted-Sum-Power-Delay-Min-WLAN problem is given by:

$$\begin{aligned} \underset{\Lambda, \Theta}{\text{minimize}} \quad & C_t^W(\Lambda, \Theta) = \alpha \sum_{i \in I, j \in J} (a\pi_j^W + b)\lambda_{i,j} \\ & + \beta\beta' \sum_{i \in I, j \in J, k \in K} \left(\frac{\lambda_{i,j}\theta_{i,k}}{\chi_{i,j,k}} + \sum_{k'=1, k' \neq k}^{N_u} \frac{\lambda_{i,j}\theta_{i,k}\theta_{i,k'}}{\chi_{i,j,k'}} \right). \end{aligned} \quad (5.3)$$

5.3 Heuristic Algorithm for the Power-Delay Minimization Problem in WLANs

The main challenge we face is the high computational complexity of the optimal solution of the Weighted-Sum-Power-Delay-Min-WLAN problem. Our purpose is to come up with a heuristic that gives efficient solution applicable for practical implementations. The proposed heuristic aims to compute the transmit power level of the BSs deployed in the network and associate UEs with these BSs in a way that jointly minimizes the total network power and the total network delay. We thus decompose the power-delay minimization problem into two sub-problems, (i) BS operation mode problem and (ii) user association problem, and tackle these problems one by one. In the former problem, the heuristic starts with an initial network state where all BSs transmit at the highest power level. Then, it changes iteratively the transmit power level of candidate BSs. In the latter problem, the heuristic seeks to associate UEs with the best BS, for each change in any BS transmit power level. The selection of the best BS takes into account the peak rate perceived by the UE and the number of covered UEs. The heuristic algorithm stops when no more improvement can be achieved in terms of power and delay reduction.

Algorithm 1 Heuristic Algorithm for the Power-Delay Minimization Problem

```

1: Input:  $N_{bs}, N_l, N_u$ .
2: Initialize  $I_1 = \{1, \dots, N_{bs}\}$ ,  $I_2 = I_3 = \dots = I_{N_l} = \emptyset$ ,  $L = [N_l, N_l-1, \dots, 2]$  and  $i_{cand} = t_{cand} = \emptyset$ ;
3: for  $l \in L$  do
4:   while (1) do
5:      $(i_{cand}, t_{cand}) = \text{SearchForBS}(I_{l-(N_l-1)}, l)$ ;
6:     if  $i_{cand} \neq \emptyset$  then
7:        $(i^*, t^*) = \min_{(i,t) \in (i_{cand}, t_{cand})} t_{cand}$ ;
8:        $I_{l-(N_l-1)} \leftarrow I_{l-(N_l-1)} \setminus \{i^*\}$ ;
9:        $I_l \leftarrow I_l \cup \{i^*\}$ ;
10:      if  $I_{l-(N_l-1)} == \emptyset$  then
11:        break;
12:      end if
13:    else
14:      break;
15:    end if
16:  end while
17: end for
18: Output:  $\lambda_{i,j}, \theta_{i,k} \forall (i, j, k) \in (I, J, K)$ .

```

Algorithm 1 describes the different steps of our heuristic algorithm for the Power-Delay minimization problem. Let I_j , $j \in J$, be the set of BSs transmitting at level j . The algorithm takes as inputs the number of BSs, the number of transmit power levels, and the number of UEs in the network (Step 1). The algorithm outputs the transmit power levels of the BSs and the user association (Step 18). The algorithm starts with an initial network state where all BSs transmit at the highest power level (Step 2), *i.e.*, $\lambda_{i,1} = 1$, $\forall i \in I$ and $\lambda_{i,j} = 0$, $\forall (i, j) \in (I, J - \{1\})$. The algorithm is composed of $(N_l - 1)$ phases (Step 3). In the first phase ($l = N_l$), the SearchForBS function (in Step 5) finds a set of candidate BSs (i_{cand}) to switch off. Starting from this set, the algorithm chooses to switch off BS i^* which results in minimizing the total network delay (Step 7). We note that, the minimum total network delay t^* is computed according to (5.2). The algorithm proceeds to the second phase as soon as no further BSs can be switched-off (Step 10). Then, the algorithm proceeds in the same way in the subsequent phases ($l = N_l - 1$ to 2), where the SearchForBS function finds a set of candidate BSs to change their transmit power level successively from $((N_l - 1)$ to 2) according to the value of l . The algorithm stops when no more BSs can reduce their transmit power level (*i.e.*, $i_{cand} = \emptyset$). In fact, this stopping condition is guaranteed to be

Algorithm 2 SearchForBS Function

```

1: Input:  $I_{fun}, l \in L = \{N_l, N_{(l-1)}, \dots, 2\}$ .
2: for  $m \in I_{fun}$  do
3:    $\lambda_{m,l} = 1$ ;
4:   if  $\forall k \in K, \exists (i, j) \in (I, J) / \chi_{i,j,k} \lambda_{i,j} \geq \chi_{threshold}$  then
5:     Compute  $\Psi_k, \forall k \in K$ ;
6:     Compute  $c(\psi), \forall \psi \in \Psi_k$ ;
7:     Compute  $\theta_{i,k} = \text{PoCo-UA}(\Psi_k, c(\psi)), \forall (i, k) \in (I, K)$ ;
8:     Compute  $C_d^W(\Lambda, \Theta)$ ;
9:      $i_{cand} \leftarrow i_{cand} \cup \{m\}$ ;
10:     $t_{cand} \leftarrow t_{cand} \cup \{C_d(\Lambda, \Theta)\}$ ;
11:   else
12:     $\lambda_{m,l} = 0$ ;
13:   end if
14: end for
15: Output:  $i_{cand}, t_{cand}$ .

```

attained, because our heuristic works in a top-down manner. Particularly, in the different phases of the algorithm, the heuristic only changes the BSs operation modes from high transmit power level to low transmit power level.

5.3.1 SearchForBS Function

Algorithm 2 describes the different steps of the SearchForBS function. This function finds a set of candidate BSs to reduce their transmit power while satisfying the coverage constraint for all UEs in the network. It takes as an input the set of network BSs transmitting at a given transmit power level (I_{fun}) and the value of the transmit power level to be applied $l \in L = \{N_l, (N_l - 1), \dots, 2\}$. The function outputs the set of candidate BSs that it has reduced the transmit power level according to the value of l , denoted by i_{cand} , and the set of total network delay resulting after changing the operation mode of each of the candidate BSs, denoted by t_{cand} (Step 15). Firstly, the function changes the transmit power level of each BS m in I_{fun} (Step 2), according to the value of l (Step 3), and verifies the coverage constraint for all UEs in the network (Step 4). Secondly, if all network UEs are covered, it computes the set of BSs covering UE k denoted by Ψ_k , and the number of UEs covered by BS ψ denoted by $c(\psi)$. Afterwards, the function associates each UE with the active BSs according to PoCo-UA (Step 7), and it computes the total network delay $C_d^W(\Lambda, \Theta)$ according to (5.2) (Step 8). Finally, BS m and the resulting total network delay are

added respectively to the sets (i_{cand}, t_{cand}) (Steps 9 and 10). Otherwise, the BS keeps its previous transmit power level (Step 12).

5.3.2 Power-Coverage Based User Association (PoCo-UA)

For the challenging user association problem [23, 22], we propose a heuristic algorithm called Power-Coverage Based User Association (PoCo-UA). The proposed heuristic PoCo-UA takes into account the peak rate perceived by the UE and the number of covered UEs at the BS side. Besides, we add uncertainty to the association in such a way that the probability to associate with a given BS is proportional to the peak rate perceived by the UE and inversely proportional to the number of covered UEs by the corresponding BS. Thus, the higher the perceived peak rate from the BS and the lower the number of covered UEs by the BS are, the higher will be the UE probability to be associated to this BS.

In fact, in Po-UA, UEs are associated with the BS delivering the highest SNR (peak rate). In our work [22], we proposed a probabilistic-peak-rate based heuristic that avoids the rush on the BS delivering better peak rate, by adding an uncertainty to the selection. In this thesis, the proposed power-coverage based user association is an enhanced version of the probabilistic-peak-rate heuristic. Precisely, it considers an additional important metric for selecting the serving BS: the number of covered UEs at the BS side.

Algorithm 3 describes the different steps of PoCo-UA. The PoCo-UA algorithm takes as inputs the set of BSs covering UE k denoted by Ψ_k , and the number of UEs covered by BS ψ denoted by $c(\psi)$ (Step 1). It outputs the user association denoted by $\Theta_{PoCo-UA}$ (Step 15). For UEs covered by several BSs (Step 4), the algorithm proceeds as follows: each UE k computes two coefficients r_k^ψ and ρ_ψ^k for each of its covering BS $\psi \in \Psi_k$ (Step 6). These coefficients take into consideration the peak rate perceived by the UE from the covering BS and the number of UEs covered by this BS, respectively. We combine these coefficients with a probability function in such a way that the probability to be associated with a given BS is proportional to the peak rate perceived by the UE and inversely proportional to the number of UEs covered by the corresponding BS. The probability for UE k to be associated with BS ψ is given by $\delta_{\psi,k}$ (Step 7). $\delta_{\psi,k}$ is added to the set of probabilities of UE k to be associated with its covering BSs, denoted by Δ_k (Step 8). Finally, UE k will be associated with the randomly drawn ψ_k^* according to these probabilities (Step 10).

The complexity of executing PoCo-UA algorithm is in $\mathcal{O}(N_u \times |\Psi_k| \log |\Psi_k|)$. The complexity of executing the heuristic algorithm for the Power-Delay minimization problem (Algorithm 1) corresponds to the complexity of executing PoCo-UA at each change of the transmit power level

Algorithm 3 Power-Coverage based User Association

```

1: Input:  $\Psi_k, c(\psi), \psi \in \Psi_k$ .
2: Initialize  $\Delta_k = \emptyset$ .
3: for  $k \in K$  do
4:   if  $|\Psi_k| \neq 1$  then
5:     for  $\psi \in \Psi_k$  do
6:       Compute  $r_k^\psi = \frac{\chi_{\psi,j,k}}{\sum_{\psi \in \Psi_k} \chi_{\psi,j,k}}, \rho_\psi^k = \frac{c(\psi)}{\sum_{\psi \in \Psi_k} c(\psi)}$ ;
7:       Compute  $\delta_{\psi,k} = \frac{r_k^\psi / \rho_\psi^k}{\sum_{\psi \in \Psi_k} r_k^\psi / \rho_\psi^k}$ ;
8:        $\Delta_k \leftarrow \Delta_k \cup \{\delta_{\psi,k}\}$ ;
9:     end for
10:     $\psi_k^* = \text{Random}(\Psi_k, \Delta_k) \Rightarrow \theta_{PoCo-UA} = \theta_{\psi_k^*,k} = 1$ ;
11:   else
12:     $\psi_k^* = \{\Psi_k\} \Rightarrow \theta_{PoCo-UA} = \theta_{\psi_k^*,k} = 1$ ;
13:   end if
14: end for
15: Output:  $\Theta_{PoCo-UA}$ ;
```

for each BS. Hence, the complexity of Algorithm 1 is in:

$$\mathcal{O}(N_u \times |\Psi_k| \log |\Psi_k| \times N_l \times N_{bs}). \quad (5.4)$$

In order to evaluate the efficiency of the heuristic algorithm for the Power-Delay minimization problem, we compare the results obtained by this heuristic with the optimal solution and existing solutions.

5.4 Existing Approaches

In this chapter, we consider two existing approaches. The first approach, which is based on legacy networks, is Po-UA/HPL provided in Section 4.5 in Chapter 4. We recall that Po-UA/HPL approach is based on legacy WLANs where BSs transmit at a fixed power level and UEs are associated with the BS delivering the highest SNR [61]. Therefore, in Po-UA/HPL, we assume that all BSs transmit at the highest power level. In this case, all UEs are thus covered by at least one BS and they are associated with the BS delivering the highest SNR.

The second approach is based on the existing approaches that consist in minimizing the total network power while ensuring the coverage constraint for all network UEs. It also considers the power adjustment capability of the BS as in our approach. $\rho_{i,j,k}$ denotes the parameter indicat-

ing whether UE k is covered by BS i transmitting at power level j . Thus, this approach can be formulated as the following optimization problem (\mathcal{P}_1):

$$\underset{\Lambda}{\text{minimize}} \quad C_p^W(\Lambda) \quad (5.5)$$

$$\text{subject to:} \quad \sum_{j \in J} \lambda_{i,j} = 1, \quad \forall i \in I, \quad (5.6)$$

$$\sum_{i \in I, j \in J} \rho_{i,j,k} \lambda_{i,j} \geq 1, \quad \forall k \in K, \quad (5.7)$$

$$\lambda_{i,j} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J. \quad (5.8)$$

Constraints (5.6) state that every BS transmits only at one power level. Constraints (5.7) ensure that a given UE covered by at least one BS. Constraints 5.8 are the integrality constraints for the decision variable $\lambda_{i,j}$. Solving problem (\mathcal{P}_1) provides the operation mode of the network BSs. Then, UEs are associated with the BS delivering the highest SNR. We denote this approach by Po-UA/Min-Po.

For both approaches, the total network power and the total network delay are computed according to (5.1) and (5.2), respectively.

5.5 Performance Evaluation

5.5.1 Evaluation Method

In order to study the efficiency of the proposed heuristic algorithm for the Power-Delay minimization problem, we implement this algorithm in MATLAB [66]. We compare its solution with the optimal one and existing solutions Po-UA/HPL and Po-UA/Min-Po. In order to compute the optimal solution of the Weighted-Sum-Power-Delay-Min-WLAN problem, we resort to the MILP formulation. We solve the MILP Weighted-Sum-Power-Delay-Min-WLAN problem and (\mathcal{P}_1) problem using the branch-and-bound method with the GLPK solver [62]. We consider a network topology composed of nine BS ($N_{bs} = 9$) using the IEEE 802.11g technology and six UEs in each cell ($N_u = 9 \times 6 = 54$). The WLAN BSs are distributed following a grid structure and the positioning of UEs follows a random uniform distribution. Moreover, we assign adjacent BSs to different IEEE 802.11 channels to mitigate the inter-cell interference. We set the number of transmit power levels to three ($N_l = 3$). Precisely, an active BS is able to transmit at two different power levels, and when the power level equals three, the BS is switched-off. We summarize the simulation parameters in Table 5.1.

Table 5.1: Simulation parameters

Parameter	Value
N_{bs}	9
N_l	3
N_u	54
Input parameters of power consumption model	$a = 3.2, b = 10.2$ [26];
Transmit power	$\pi_1 = 0.03$ W and $\pi_2 = 0.015$ W [58]
Average power consumed per BS $i \in I$	$p_{i,1} = 10.296$ W, $p_{i,2} = 10.248$ W, and $p_{i,3} = 0$
Coverage radius for the first and second power levels	$R_1 = 107.4$ m $R_2 = 75.8$ m
Pathloss model	Free space propagation model
Carrier frequency	2400 MHz

5.5.1.1 Coverage area and peak rate computation

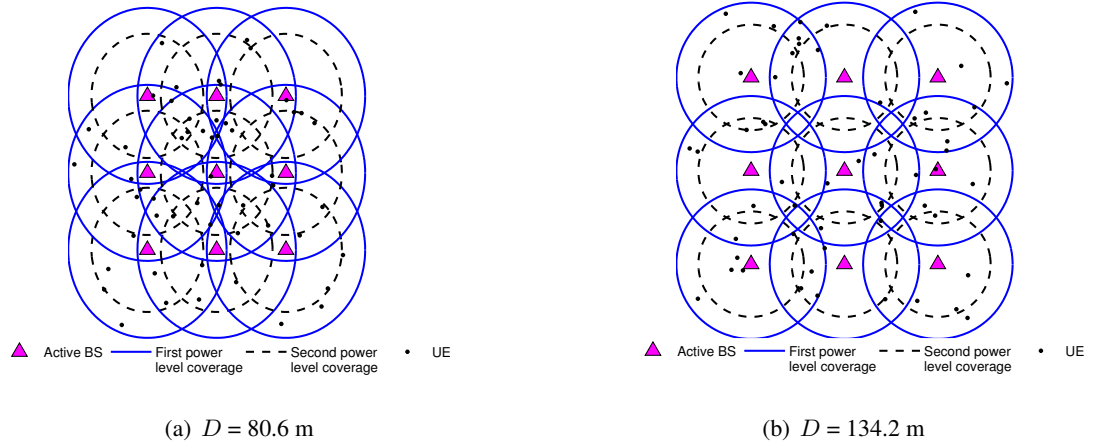
In Section 4.6.1, we introduced a benchmark scenario that enables the computation of: *i*) the peak rate perceived by the UE from the BS as a function of the distance between them and considering two different transmit powers ($\pi_1 = 0.03$ W and $\pi_2 = 0.015$ W); *ii*) the coverage radius for the first and the second power levels $R_1 = 107.4$ m and $R_2 = 75.8$ m respectively. These radii correspond to a cell edge peak rate that equals 1 Mb/s ($\chi_{th} = 1$ Mb/s) on the downlink. This peak rate is the minimum value to be maintained in order to consider that a given user is covered by a BS. It corresponds to an SNR threshold that equals -0.5 dB at the cell boundary.

In the following, the simulation results for the heuristic and optimal solutions are plotted as a function of the inter-cell distance D . For small inter-cell distances, we obtain a dense coverage area, while large inter-cell distances produce sparse coverage area. Table 5.2 shows the average number of covering BSs per UE as a function of the inter-cell distance. For $D = 80.55$ m, we obtain a dense coverage area where the average number of covering BSs per UE is 3.4. As D increases, the average number of covering BSs per UE decreases to reach 1 when there is no overlap between cells ($D = 2R_1$). Figure 5.1 shows an example of the network topology for inter cell distances $D = 80.6$ m and $D = 134.2$ m.

Furthermore, we only consider the case where $\alpha = \beta = 0.5$ in (5.3). Such case balances the tradeoff between minimizing power and delay. Moreover, the normalization factor β' is calculated in each simulation in such a way to scale the total network power and the total network delay as explained in Section 3.4.3.2 in Chapter 3. For the results of the MILP Weighted-Sum-Power-

Table 5.2: Covering BSs per UE VS. inter-cell distance.

Inter-cell distance [m]	Number of covering BSs per UE
80.6	3.40
93.98	2.78
107.4	2.40
120.8	2.02
134.2	1.76
147.6	1.53
161.1	1.38
174.5	1.25
187.9	1.15
201.3	1.05
214.8	1.00

Figure 5.1: Examples of the network topology with $N_{bs} = 9$, $N_l = 3$ and $N_u = 54$.

Delay-Min-WLAN problem and Po-UA/Min-Po approach, we adopt the Monte Carlo method by generating 50 snapshots with different random uniform UE distribution. After computing all the snapshots, we provide the 95% Confidence Interval (CI) for each simulation result. For the heuristic results, we run the heuristic algorithm (Algorithm 1) five times on each of the 50 snapshots and illustrate the 95% CI. Precisely, the obtained heuristic solution depends on the order in which the algorithm iterates through the different network elements. Moreover, the user association problem is a very challenging one. Therefore, in each iteration of the heuristic algorithm, we run the PoCo-UA user association (Algorithm 3) 50 times and select the best $\Theta_{PoCo-UA}$ that gives the minimal total network delay.

5.5.2 Simulation Results

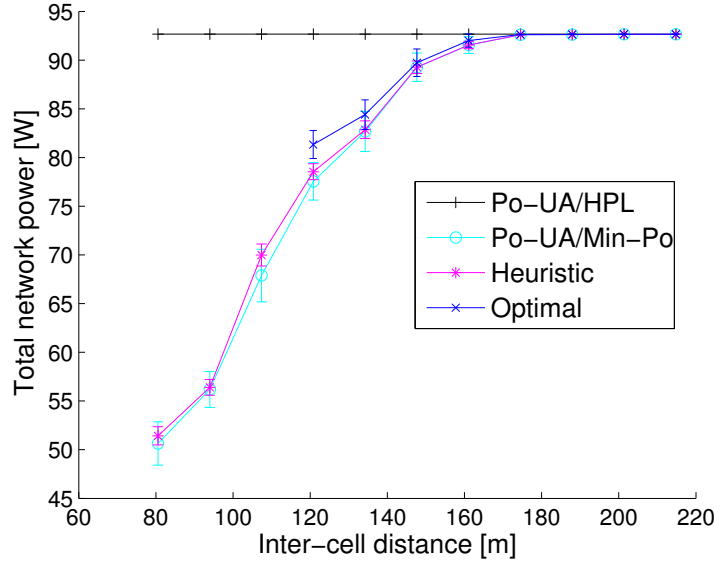


Figure 5.2: Total network power for heuristic, optimal, Po-UA/HPL and Po-UA/Min-Po solutions.

We plot in Fig. 5.2, the total network power for the heuristic, optimal, Po-UA/HPL and Po-UA/Min-Po solutions as a function of the inter-cell distance D . Note that the total network power is computed according to (5.1). In Po-UA/HPL approach, all BSs transmit at the highest power level. This explains why Po-UA/HPL model has the highest total network power for all D . Moreover, results show that the heuristic solution outperforms the optimal one for D ranging between 120.8 m to 161.1 m. In addition, for dense networks (*i.e.*, $D \leq 120.8$ m), the heuristic has low computational complexity whereas the optimal solution cannot be computed. The proposed heuristic performs close to Po-UA/Min-Po approach which minimizes the total network power while ensuring coverage for all UEs. The heuristic and Po-UA/Min-Po solutions provide power savings up to 45% compared with Po-UA/HPL for $D = 80.6$ m. Finally, the heuristic, optimal and Po-UA/Min-Po solutions show increasing curves for $D \leq 161.1$ m. Then, the total network power for these solutions becomes constant and equals the total network power for the Po-UA/HPL model for $D \geq 161.1$ m.

5.5.2.0.1 Power Saving Compared with Po-UA/HPL To examine the cause of power savings in the heuristic, optimal and Po-UA/Min-Po solutions compared with Po-UA/HPL model for $D \leq 161.1$ m, we plot the percentage of the BS operation modes in Fig. 5.3. For the optimal solution, results are provided for D ranging between 120.8 m to 161.1 m, as the optimal solution has high computational complexity for dense networks (*i.e.*, $D \leq 120.8$ m). For the heuristic

and Po-UA/Min-Po solutions, results are provided for D ranging between 80.6 m to 161.1 m. We notice that in the heuristic solution, the percentage of switched-off BSs and the percentage of BSs transmitting at the second power level is greater than that in the optimal solution for D ranging between 120.8 m to 161.1 m. The reason for this is that the proposed heuristic has an aggressive power saving policy: it switches off iteratively the maximum number of possible BSs then it reduces iteratively the transmit power level of the remaining possible BSs, while associating users to the active BSs in such a way to obtain in each iteration the minimum total network delay. However, the optimization problem minimizes simultaneously the total network power and the total network delay. This explains why we obtain a solution where the total network power is higher than the heuristic one.

We notice that the heuristic and Po-UA/Min-Po solutions have almost the same percentage of BS operation mode. This validates the aggressive power saving policy of the proposed heuristic algorithm.

Moreover, for the considered solutions, we see that when D increases the percentage of switched-off BSs decreases, and the percentage of BSs transmitting at the second power level increases. Precisely, for small values of D (*i.e.*, 80.6 m), the number of covering BSs per UE is relatively high (*i.e.*, 3.4 as shown in Tab. 5.2); thus, a large number of BSs can be switched-off or can transmit at low power level (*i.e.*, 44% of the BSs are switched-off as shown in Fig. 5.3(a) and Fig. 5.3(c). However, when the value of D increases, the number of covering BSs per UE decreases and thus the possibility to switch off an BS or to transmit at low power level decreases in order to ensure coverage for all UEs in the network. This explains the increasing curves for the corresponding inter-cell distances in Fig. 5.2. Also, this logic validate why we obtain in these solutions a total network power equal to the one in Po-UA/HPL model for large D (*i.e.*, $D \geq 161.1$ m) in the same figure.

We now investigate the total network delay for the heuristic, optimal, Po-UA/HPL and Po-UA/Min-Po solutions while varying the inter-cell distance. The total network delay is computed according to (5.2). Figure 5.4 shows that the Po-UA/HPL model has the lowest total network delay followed successively by the optimal solution, heuristic solution and then by Po-UA/Min-Po solution. Precisely, in the Po-UA/HPL approach, all BSs transmit at the highest power level. This implies that all UEs perceive a relatively high SNR which lowers the total network delay. While for the heuristic solution, the number of BSs transmitting at low level or switched-off is greater than that of the optimal one (as shown in Fig. 5.3). This causes the total network delay of the heuristic to be higher than the optimal one. Even though, the proposed heuristic and Po-UA/Min-Po approach have the same performance in terms of power saving (as shown in Fig. 5.3), the heuristic outperforms Po-UA/Min-Po approach in terms of delay reduction. This is because, the former associates

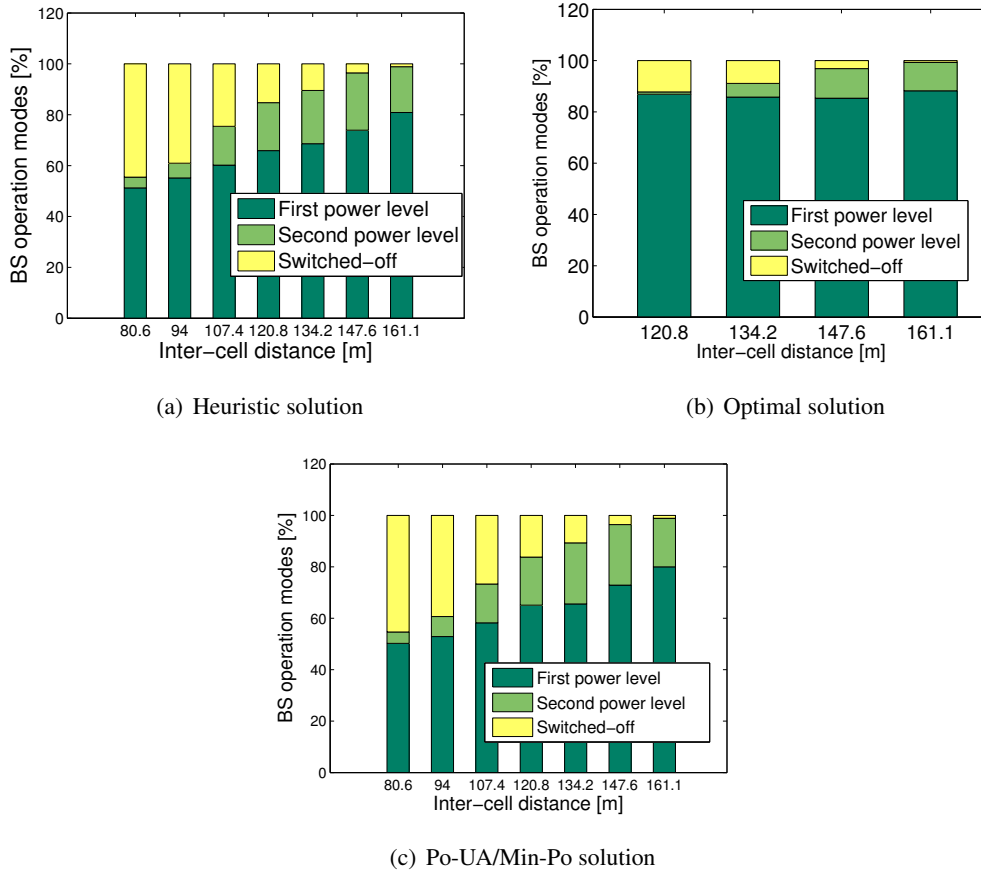


Figure 5.3: Percentage of BS operation modes in heuristic, optimal and Po-UA/Min-Po solutions.

the UEs with the network BSs in a way that minimizes the total network delay, whereas the latter associates UEs with the BS delivering the highest SNR without considering delay minimization. Moreover, we see that the total network delay for the optimal solution and for Po-UA/HPL model have increasing curves. Precisely, for the same UE distribution, when D increases, the SNR of the UE decreases, which causes the delay to increase. Whereas, the heuristic and Po-UA/Min-Po solutions have decreasing curves for D between 80.6 m and 161.1 m then the curves become increasing for $D \geq 161.1$ m. Typically, for D between 80.6 m and 161.1 m, the number of BSs transmitting at either the highest power level or the second power level increases (as shown in Fig. 5.3(a) and Fig. 5.3(c)) and thereby UEs experience a lower delay.

Note that all the curves converge to the same point. Precisely, for high values of inter-cell distance ($D \geq 161.1$ m), the simulated algorithms converge to a solution where all BSs transmit at the highest power level. This corresponds to the only feasible solution of the Power-Delay minimization problem. In this situation, this problem boils down to a user association that minimizes the sum of UE transmission delays.

Finally, in order to study the computational complexity of the heuristic algorithm, we depict in

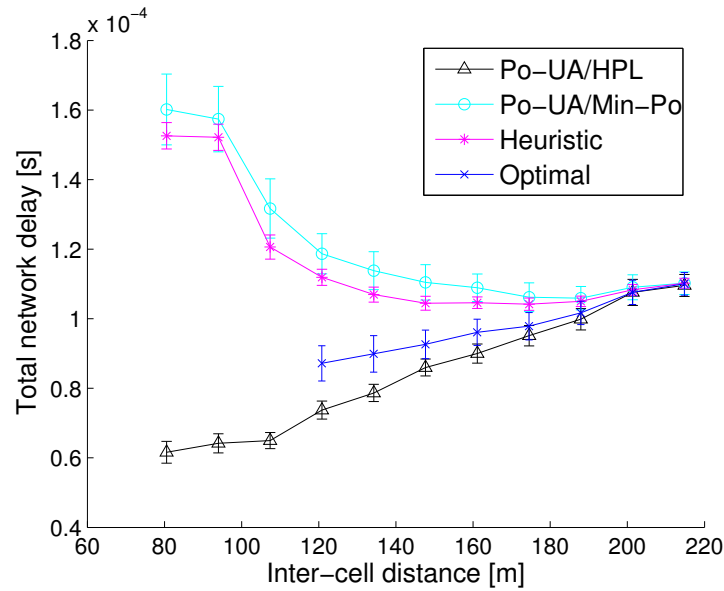


Figure 5.4: Total network delay for heuristic, optimal, Po-UA/HPL and Po-UA/Min-Po solutions.

Tab. 5.3 the computation time of the heuristic, optimal, Po-UA/HPL and Po-UA/Min-Po solutions as a function of the inter-cell distance. On the one hand, results show that the heuristic solution has a low computational time for dense networks compared with the optimal solution. For instance, for D equals 80.6 m, it takes 11.89 sec of computation time, whereas the optimal solution cannot be computed. We notice that for D equals 128.08 m, the heuristic algorithm has a negligible computation time compared to the optimal one. Moreover, the computation time decreases when D increases. In particular, the complexity of executing the heuristic algorithm depends on the number of covering BSs per user according to (5.4). As shown in Tab. 5.2, when D increases, the number of covering BSs per UE decreases causing the computation time to decrease. On the other hand, the computation time is relatively high compared with existing approaches: this is because in each iteration of the heuristic algorithm, the user association is obtained after 50 runs of Algorithm 3. In fact, if we decrease the number of runs of Algorithm 3, the computational time of the heuristic algorithm will decrease but the quality of the solution will be affected. We note that, for Po-UA/Min-Po, the presented time accounts for the time necessary to solve problem (\mathcal{P}_1) and the time for user association. The former is provided by GLPK solver and it is negligible. The latter is provided by MATLAB, and it depends on the number of covering BS per UE. For low inter-cell distance, the percentage of switched-off BS is relatively high (as shown in Fig. 5.3(c)), which causes the number of covering BS per UE to be low. This explains why, for $D \leq 107.4$ m, the computation time of Po-UA/Min-Po solution is lower than that of Po-UA/HPL solution.

Table 5.3: Computation time in [s]

Inter-cell distance [m]	80.6	93.98	107.4	120.8
Heuristic solution	11.8853	9.6425	7.1794	4.5662
Optimal solution	N/A	N/A	N/A	1091.90
Po-UA/HPL	0.0113	0.0100	0.0099	0.0095
Po-UA/Min-Po	0.0023	0.0023	0.0023	0.0120

5.6 Conclusion

In this chapter, we proposed a heuristic algorithm for the joint Power-Delay minimization problem in WLANs. Our goal was to come-up with a heuristic that has low computational complexity and provides a satisfactory solution. Simulation results showed that the proposed heuristic gives comparable power savings with respect to optimal and existing schemes. Moreover, in dense scenarios, the optimal solution is intractable whereas the heuristic algorithm provides efficient results that show significant power savings of up to 45% compared with legacy solutions in a reasonable time. However, for both solutions, the network power is saved at the cost of an increase in network delay. In addition, for sparse scenarios, there is no substantial gain compared with legacy network model and thus power saving is superfluous.

Part II

Joint Minimization of Power and Delay in 4G Wireless Networks

**Minimization of Power and
Delay in 4G Wireless
Networks****6.1 Introduction**

The global LTE market has evolved considerably since the launch of the first network in Sweden in December 2009. It is now moving to a more mature phase of development with around 230 commercial LTE networks now in operation and over one billion connections expected by 2017 [67]. Starting from this premise, we consider that the problem of joint power-delay minimization in 4G networks is a topic worth investigating in this thesis. Thus, in this part, we cover the LTE technology considering the EARTH model for BS power model and the fair-time sharing model for radio resource allocation. Power saving is achieved by adjusting the operation mode of the network BSs from high transmit power levels to low transmit levels or sleep mode. Minimizing the transmission delay is achieved by selecting the best user association with the network BSs. Particularly, in the present chapter, we formulate the power-delay minimization in 4G networks as a non-linear problem. Then, we transform it to a MILP problem following the method presented in Section 4.4.1 in Chapter 4. Finally, we provide extensive simulations for various decision preferences such as power minimization, delay minimization and joint minimization of power and delay. We consider rural and urban deployments, and assess the impact of the end users position in the cell on the achievable tradeoffs.

The rest of the chapter is organized as follows. In Section 6.2, we describe the network model considering an LTE network. In Section 6.3, we present the scalar power-delay minimization problem in LTE networks. We then present the MILP formulation in Section 6.4. In Section 6.5,

we provide extensive simulation results. Conclusions are given in Section 6.6.

6.2 Nework Model

In this chapter, we consider a 4G wireless network with N_{bs} BSs. We assume that each BS operates in two modes: active mode and sleep mode. We consider the same assumptions provided in Chapter 4. Specifically, we only consider the downlink traffic and elastic traffic model. In fact, downlink and uplink performance can be jointly considered in our approach. Precisely, In the Full Division Duplexing (FDD) mode, there are two carrier frequencies, one for uplink transmission and one for downlink transmission. Thus, FDD divides the frequency band allotted into two discrete smaller channels for both uplink and downlink [68]. Further, the LTE uplink is on based SC-FDMA (Single Carrier-Frequency Division Multiple Access), which is a modified version of an OFDMA technology (used in LTE downlink). We also assume that *i*) the network is in a static state where UEs are stationary, *ii*) the network is in a saturation state.

In LTE networks, OFDMA is adopted as the downlink access method, which allows multiple UEs to transmit simultaneously on different subcarriers. As subcarriers are orthogonal, intra-cell interference is highly reduced. However, inter-cell interference is a key issue in OFDMA networks that greatly limits the network performance, especially for users located at the cell edge. One of the fundamental techniques to deal with the inter-cell interference problem is to control the use of frequencies over the various channels in the network [69]. There are three major frequency reuse patterns for mitigating inter-cell interference: hard frequency reuse (such as frequency reuse 1 and 3), fractional frequency reuse and soft frequency reuse fractional [70].

Hard frequency reuse splits the system bandwidth into a number of distinct sub-bands according to a chosen reuse factor and neighboring cells transmit on different sub-bands. For instance, Frequency Reuse 3 scheme consists of dividing the frequency band into three sub-bands and allocating only one sub-band to a given cell, in such a way that the adjacent cells use different frequency bands. Compared with frequency reuse 1, this scheme leads to low interference with at the cost of a capacity loss because only one third of the resources are used in each cell [71]. In this thesis, we adopt the Frequency Reuse 3 scheme to mitigate the inter-cell interference. The main notations used in this chapter are reported in Table 6.1.

6.2.1 Data Rate and delay models in LTE Networks

In OFDMA, the system spectrum is divided into a number of consecutive orthogonal OFDM subcarriers. The Resource Block (RB) is the smallest resource unit that can be scheduled. The RB

Table 6.1: Notation Summary

Notation	Definition
I	Set of network BSs
J	Set of transmit power levels of a given BS
K	Set of UEs in the network
N_{bs}	The total number of BSs
N_l	The total number of transmit power levels
N_u	The total number of UEs
$p_{i,j}$	The average consumed power per BS i transmitting at power level j
π_j^L	The transmit power at level j for LTE BSs
$\chi_{i,j,k}$	The peak rate perceived by UE k from BS i transmitting at level j
$T_{i,j,k}^L$	The transmission delay of UE k associated with LTE BS i transmitting at level j
$\theta_{i,k}$	A binary variable that indicates if UE k is associated with BS i
$\lambda_{i,j}$	A binary variable that indicates if BS i transmits at power level j
$y_{i,j,k}$	A binary variable that indicates if UE k is associated with BS i transmitting at power level j
$z_{i,j,k,k'}$	A binary variable that indicates if UE k and UE k' are associated with BS i transmitting at power level j

consists of 12 consecutive subcarriers for one slot (0.5 msec) in duration. In this thesis, we consider a flat channel model where each UE has similar radio conditions on all the RBs. We consider a fair-time sharing scheduling where RBs are assigned with equal time to UEs within a given cell. In fact, this corresponds to the widely used OFDMA in LTE with a round robin scheduler [72] that assigns RBs cyclically to UEs within a given cell. This resource sharing policy ensures temporal fairness. Based on these considerations and on UEs being stationary, the scheduler is equivalent to one that allocates periodically all RBs to each UE at each scheduling epoch. Hence, when UE k is associated with BS i transmitting at level j , its mean throughput $R_{i,j,k}^L$ depends on its peak rate $\chi_{i,j,k}$ and on the number of UEs associated with the same BS. $R_{i,j,k}^L$ is given by [23]:

$$R_{i,j,k}^L = \frac{\chi_{i,j,k}}{1 + \sum_{k'=1, k' \neq k}^{N_u} \theta_{i,k'}}, \quad (6.1)$$

where $\theta_{i,k'}$ is the binary variable indicating whether or not UE k' is associated with BS i . Let $T_{i,j,k}^L$ denote the transmission delay of UE k from BS i transmitting at level j in the case of an LTE network. $T_{i,j,k}^L$ is given by:

$$T_{i,j,k}^L = \frac{1 + \sum_{k'=1, k' \neq k}^{N_u} \theta_{i,k'}}{\chi_{i,j,k}}. \quad (6.2)$$

6.2.2 Power Consumption Model in LTE Networks

Following the model proposed in the EARTH project [1], the power consumption of a BS is modeled as a linear function of the average transmit power as below:

$$\forall i \in I, p_{i,j}^L = \begin{cases} N_{TRX}(v\pi_j^L + w_j), & 0 < \pi_j^L \leq \pi_1^L, \quad j = 1, \dots, (N_l - 1); \\ N_{TRX}w_{N_l}, & \pi_{N_l}^L = 0. \end{cases} \quad (6.3)$$

where $p_{i,j}^L$ and π_j^L denote the average consumed power per LTE BS i and the transmit power at level j respectively. For $j = 1$, we consider that the BS transmits at the highest power level, and for $j = N_l$, the BS is in sleep mode. The coefficient v is the slope of the load-dependent power consumption and it accounts for the power consumption that scales with the transmit power due to radio frequency amplifier and feeder losses. The coefficients w_j ($j = 1, \dots, (N_l - 1)$) represent the power consumption at zero output power (it is actually estimated using the power consumption calculated at a reasonably low output power, assumed to be 1% of p_1^L). These coefficients model the power consumed independently of the transmit power due to signal processing, power supply consumption and cooling. w_{N_l} is a coefficient that represents the sleep mode power consumption. N_{TRX} is the number of BS transceivers.

6.3 Power-Delay Minimization Problem in 4G Wireless Networks

in order to study the tradeoffs between minimizing the power consumption of the network and minimizing the sum of users delay in LTE networks, we resort to the Weighted Sum Method. We denote by Weighted-Sum-Power-Delay-Min-LTE the scalar optimization problem for LTE networks. Let C_p^L , C_d^L and C_t^L denote the total network power, the total network delay and the total network cost for this case, respectively. C_p^L and C_d^L are obtained from (3.8) and (3.9) by replacing $p_{i,j}$ and $T_{i,j,k}$ by the expressions of $p_{i,j}^L$ and $T_{i,j,k}^L$, respectively. Therefore,

$$C_p^L(\Lambda) = \sum_{i \in I, j \in J} N_{TRX}(v\pi_j^L + w_j)\lambda_{i,j}, \quad (6.4)$$

$$C_d^L(\Lambda, \Theta) = \sum_{i \in I, j \in J, k \in K} \frac{\lambda_{i,j}\theta_{i,k} + \sum_{k'=1, k' \neq k}^{N_u} \lambda_{i,j}\theta_{i,k}\theta_{i,k'}}{\chi_{i,j,k}}, \quad (6.5)$$

$$C_t^L(\Lambda, \Theta) = \alpha C_p^L(\Lambda) + \beta \beta' C_d^L(\Lambda, \Theta). \quad (6.6)$$

The Weighted-Sum-Power-Delay-Min-LTE problem consists of finding the optimal transmit power level of the BSs deployed in the network and optimal user association that minimize the

total network cost C_t^L . Consequently, the Weighted-Sum-Power-Delay-Min-LTE problem is given by:

$$\begin{aligned} \underset{\Lambda, \Theta}{\text{minimize}} \quad & C_t^L(\Lambda, \Theta) = \alpha \sum_{i \in I, j \in J} N_{TRX}(v\pi_j^L + w_j)\lambda_{i,j} \\ & + \sum_{i \in I, j \in J, k \in K} \frac{\lambda_{i,j}\theta_{i,k} + \sum_{k'=1, k' \neq k}^{N_u} \lambda_{i,j}\theta_{i,k}\theta_{i,k'}}{\chi_{i,j,k}}, \end{aligned} \quad (6.7)$$

$$\text{subject to: } \sum_{j \in J} \lambda_{i,j} = 1, \quad \forall i \in I, \quad (6.8)$$

$$\sum_{i \in I} \theta_{i,k} = 1, \quad \forall k \in K, \quad (6.9)$$

$$\lambda_{i,j} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J, \quad (6.10)$$

$$\theta_{i,k} \in \{0, 1\}, \quad \forall i \in I, \forall k \in K, \quad (6.11)$$

$$\theta_{i,k} = 0, \quad \forall i \in I, \forall k \in K / \chi_{i,1,k} \leq \chi_{th}, \quad (6.12)$$

$$\lambda_{i,N_l}\theta_{i,k} = 0, \quad \forall i \in I, \forall k \in K, \quad (6.13)$$

$$\lambda_{i,j}\theta_{i,k} = 0, \quad \forall i \in I, \forall j \in \{2, \dots, N_l - 1\}, \forall k \in K / \chi_{i,j,k} \leq \chi_{th}. \quad (6.14)$$

Constraints (6.8) state that each BS transmits at only one power level. Constraints (6.9) ensure that a given UE is associated with only one BS. Constraints (6.10) and (6.11) are the integrality constraints for the decision variables $\lambda_{i,j}$ and $\theta_{i,k}$. Constraints (6.12) prevent a given UE from being associated with a BS if that UE is not in the BS's first power level coverage area. Constraints (6.13) prevent UEs from being associated with a BS in sleep mode. Constraints (6.14) prevent a given UE from being associated with a BS if the former is not in the BS's j^{th} power level coverage area.

6.4 Mixed Integer Linear Programming Formulation

The Weighted-Sum-Power-Delay-Min-LTE problem is a binary non-linear optimization problem. In this section, we present the MILP formulation of the problem following the formulation method presented in Section 4.4.1 in Chapter 4. Particularly, in the objective function (6.7) and in the constraints (6.13) and (6.14), we replace the non-linear terms $\lambda_{i,j}\theta_{i,k}$ and $\lambda_{i,j}\theta_{i,k}\theta_{i,k'}$ by new linear variables $y_{i,j,k}$ and $z_{i,j,k,k'}$, respectively, and add inequality constraints. The additional constraints ensure that the new variables behave according to the non-linear terms they are replacing. We note that $y_{i,j,k}$ and $z_{i,j,k,k'}$ are respectively the elements of the matrices Y and Z . Therefore,

our MILP Weighted-Sum-Power-Delay-Min-LTE problem is given by:

$$\begin{aligned} \underset{\Lambda, Y, Z}{\text{minimize}} \quad & C_t^L(\Lambda, Y, Z) = \alpha \sum_{i \in I, j \in J} N_{TRX} (v\pi_j^L + w_j) \lambda_{i,j} \\ & + \beta \beta' \sum_{i \in I, j \in J, k \in K} \frac{y_{i,j,k} + \sum_{k'=1, k' \neq k}^{N_u} z_{i,j,k,k'}}{\chi_{i,j,k}}, \end{aligned} \quad (6.15)$$

subject to: (6.8) to (6.12),

$$y_{i,N_l,k} = 0, \quad \forall i \in I, \forall k \in K, \quad (6.16)$$

$$y_{i,j,k} = 0, \quad \forall i \in I, \forall j \in \{2, \dots, N_l - 1\}, \forall k \in K / \chi_{i,j,k} \leq \chi_{th}, \quad (6.17)$$

$$y_{i,j,k} - \lambda_{i,j} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k \in K, \quad (6.18)$$

$$y_{i,j,k} - \theta_{i,k} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k \in K, \quad (6.19)$$

$$\lambda_{i,j} + \theta_{i,k} - y_{i,j,k} \leq 1, \quad \forall i \in I, \forall j \in J, \forall k \in K, \quad (6.20)$$

$$z_{i,j,k,k'} - \lambda_{i,j} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (6.21)$$

$$z_{i,j,k,k'} - \theta_{i,k} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (6.22)$$

$$z_{i,j,k,k'} - \theta_{i,k'} \leq 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (6.23)$$

$$\lambda_{i,j} + \theta_{i,k} + \theta_{i,k'} - z_{i,j,k,k'} \leq 2, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (6.24)$$

$$z_{i,j,k,k'} - z_{i,j,k',k} = 0, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K, \quad (6.25)$$

$$0 \leq y_{i,j,k} \leq 1, \quad \forall i \in I, \forall j \in J, \forall k \in K, \quad (6.26)$$

$$0 \leq z_{i,j,k,k'} \leq 1, \quad \forall i \in I, \forall j \in J, \forall k < k' \in K. \quad (6.27)$$

Constraints (6.16) and (6.17) are the constraints replacing constraints (6.13) and (6.14), respectively. Constraints (6.18 - 6.20) and constraints (6.21 - 6.24) are the additional constraints relative to the new variable $y_{i,j,k}$ and $z_{i,j,k,k'}$, respectively. Constraints (6.25) force $z_{i,j,k,k'}$ to be equal to $z_{i,j,k',k}$, because $\lambda_{i,j}\theta_{i,k}\theta_{i,k'} = \lambda_{i,j}\theta_{i,k'}\theta_{i,k}$. Constraints (6.26 and 6.27) are the bound constraints for the variables $y_{i,j,k}$ and $z_{i,j,k,k'}$, respectively.

6.5 Performance Evaluation

6.5.1 Evaluation Method

To study the tradeoff between minimizing the power consumption of the network and minimizing the sum of UE delays in 4G wireless networks, we tune the values of the weights α and β in (6.15), associated with the total network power and total network delay respectively, and investigate the obtained solutions. We consider the five settings illustrated in Tab. 6.2. Precisely, settings S1 and S2 match the case where preference is given to power saving. Setting S3 matches

the case where the power and delay are equally important. Settings S4 and S5 match the case where preference is given to minimizing delay.

Table 6.2: Five studied settings in LTE networks.

Settings	Weighting coefficients value	Description
S1	$\alpha = 0.99, \beta = 0.01$	Preference is given to saving power
S2	$\alpha = 0.75, \beta = 0.25$	
S3	$\alpha = 0.5, \beta = 0.5$	Balance the tradeoff between minimizing power and delay
S4	$\alpha = 0.25, \beta = 0.75$	Preference is given to minimizing delay
S5	$\alpha = 0.01, \beta = 0.99$	

We compute the optimal solution of the MILP Weighted-Sum-Power-Delay-Min-LTE problem using the CPLEX solver [73]. The input data for the CPLEX solver are generated using MATLAB [66]. Thus, in MATLAB, we implement an LTE network topology composed of nine cells ($N_{bs} = 9$) where the LTE BSs are transmitting using omni-directional antennas in two deployment cases: urban and rural. The positioning of the LTE BSs in the network is performed following a grid structure. The simulated LTE system bandwidth is 5 MHz. Therefore we have 25 RBs available in each cell. We assume a frequency reuse 3 scheme in the network to mitigate the inter-cell interference. Thus, the system bandwidth is divided into three equal sub-bands, each of these sub-bands is allocated to cells in a manner that no other surrounding cell is using the same sub-band. Consequently, we have 8 RBs available in each cell. The fair-time sharing model is used, and the scheduler allocates periodically all RBs to each UE at each scheduling epoch as explained in Section 6.2.1. Moreover, we assume a saturated-full buffer traffic model. The simulation parameters and the pathloss model follow those in [74, 3, 1], which are summarized in Tab. 6.3.

6.5.1.1 Propagation model

The Cost 231 extended Hata model is used for modeling the radio channel of the LTE BS in urban [3] and rural [74] environments, with a carrier frequency f of 2000 MHz. The shadowing is represented by a random variable following a normal distribution with a mean of 0 dB and a standard deviation of 10 dB. For urban deployment cases, the antenna height h_a equals 30 m, the UE height h_u equals 1.5 m, the area type correction factor C_m equals 3 dBm, and the UE-BS

Table 6.3: Simulation parameters for LTE

Parameter	Value
Input parameters of power consumption model	$N_{TRX} = 1, v = 4.7, w_1 = w_2 = 130 \text{ W } w_3 = 75 \text{ W}$
Transmit power	$\pi_1 = 10 \text{ W}, \pi_2 = 5 \text{ W } \pi_3 = 0$
Average power consumed per BS i	$p_{i,1} = 177 \text{ W}, p_{i,2} = 153.5 \text{ W}, p_{i,3} = 75 \text{ W } (i \in I)$
Transmit antenna gain	15 dBi
Receiver antenna gain	0
Coverage radius for the first and the second power levels	$R_1 = 500 \text{ m}$ $R_2 = 250 \text{ m}$
Inter-cell distance	Urban: 700 m Rural: 900 m
Pathloss model	Cost 231 extended Hata model
Shadowing standard deviation	10 dB
Carrier frequency	2000 MHz
Bandwidth	5 MHz
Frequency Reuse scheme	3
Number of RB per cell	8
Bandwidth per RB	180 KHz
Traffic model	Saturated-full buffer
Noise figure	9 dB
Thermal noise density	-174 dBm/Hz
Thermal noise power	-103.4 dBm

separation is denoted by d [Km]. Therefore, the urban pathloss L_1 is given by:

$$L_1 = 46.3 + 33.9 \times \log_{10}(f) - 13.82 \times \log_{10}(h_a) - a \\ + (44.9 - 6.55 \times \log_{10}(h_a)) \times \log_{10}(d) + C_m + \text{shadowing} \text{ [dB]}; \quad (6.28)$$

where $a = (1.1 \times \log_{10}(f) - 0.7) \times h_u - (1.56 \times \log_{10}(f) - 0.8)$.

For rural deployment cases, the antenna height equals 45 m. Therefore, the rural pathloss L_2 is given by:

$$L_2 = 69.55 + 26.16 \times \log_{10}(f) - 13.82 \times \log_{10}(h_a) + (44.9 - 6.55 \times \log_{10}(h_a)) \times \log_{10}(d) \\ - 4.78 \times (\log_{10}(f))^2 + 18.33 \times \log_{10}(f) - 40.94 + \text{shadowing} \text{ [dB]}; \quad (6.29)$$

6.5.1.2 Peak rate computation

Knowing the pathloss, the signal strength $S_{i,j,k}$ received by UE k from BS i transmitting at power level j is calculated according to:

$$S_{i,j,k} = 10 \times \log_{10}(\pi_j^L \times 1000) - (PathLoss - TransmitAntennaGain - ReceiverAntennaGain) \text{ [dBm]}. \quad (6.30)$$

The SNR detected by UE k from BS i transmitting at power level j is thus given by:

$$SNR = S_{i,j,k} - ThermalNoisePower \text{ [dB]}, \quad (6.31)$$

where the thermal noise power is given by:

$$ThermalNoisePower = 10 \times \log_{10}(1000 \times ThermalNoiseDensity \times BandwidthperRB \times NumberOfRBperCell) + NoiseFigure \text{ [dBm]}. \quad (6.32)$$

Then the spectral efficiency (in bit/s/Hz) is computed according to Fig. 6.1 in the 3GPP TR 36.942 [3]. As mentioned earlier, the scheduler allocates all RBs to one UE at each schedul-

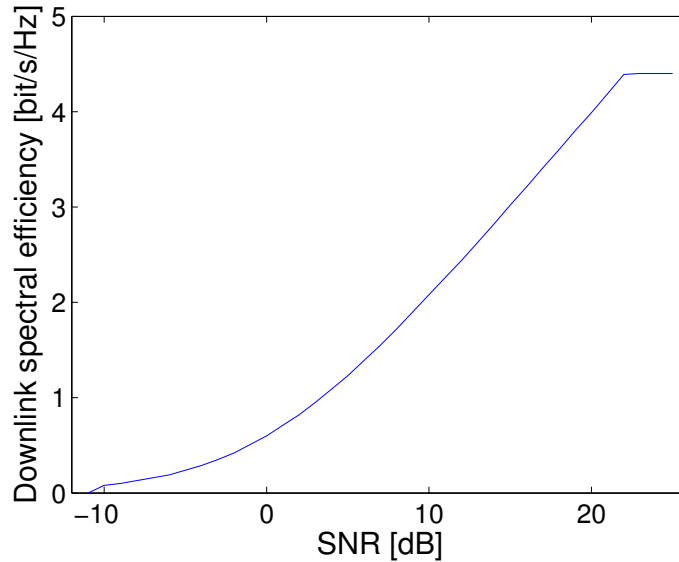


Figure 6.1: Spectral efficiency in LTE as a function of SNR [3].

ing epoch. Therefore, to compute the peak rate $\chi_{i,j,k}$ perceived by UE k from BS i transmitting at power level j in bit/s, we multiply the value obtained from Fig. 6.1 by the bandwidth per RB and by the number of RBs per cell.

We compare the performance of our MILP solution for the considered settings with the reference model Po-UA/HPL provided in Section 4.5 in Chapter 4. Po-UA/HPL is based on current

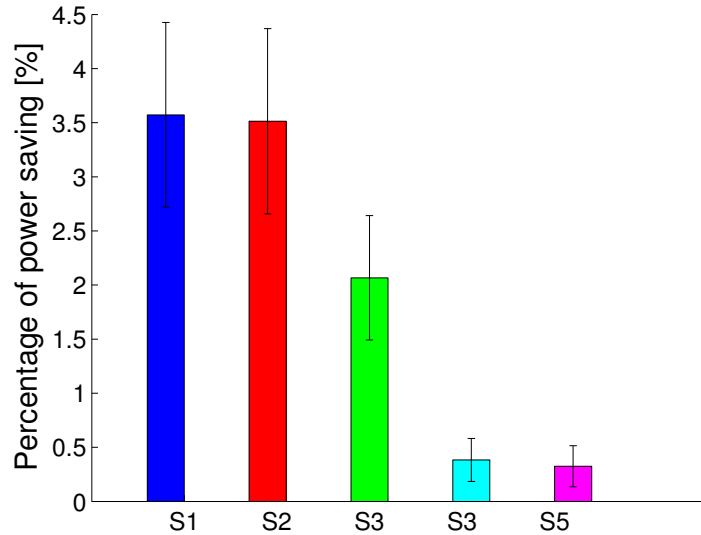


Figure 6.2: Power saving for the considered settings in LTE scenario for an urban deployment.

cellular networks where BSs transmit at a fixed power level and UEs are associated with the BS delivering the highest SNR [27]. Therefore, in Po-UA/HPL, we assume that all BSs transmit at the highest power level. In this case, all UEs are thus covered by at least one BS and they are associated with the BS delivering the highest SNR.

We adopt the Monte Carlo method by generating 50 snapshots with different random uniform UE distributions. After computing all the snapshots, we provide the 95% CI for each simulation result. Next, we consider rural and urban deployments, and assess the impact of the end UE's position in the cell on the achievable tradeoffs.

6.5.2 Simulation Results for an Urban Deployment

For the urban deployment, we consider an inter-cell distance of 700 m, and provide simulation results for both uniform and non-uniform UE distributions.

6.5.2.1 Uniform Distribution of UEs

We consider six UEs in each cell, and a total of 54 UEs ($N_u = 9 \times 6 = 54$) in the network. The positioning of UEs is generated randomly following a uniform distribution. In the present urban deployment, the mean number of covering BSs per UE equals 1.5.

We illustrate in Fig. 6.2 the percentage of power saving for the considered settings, which is

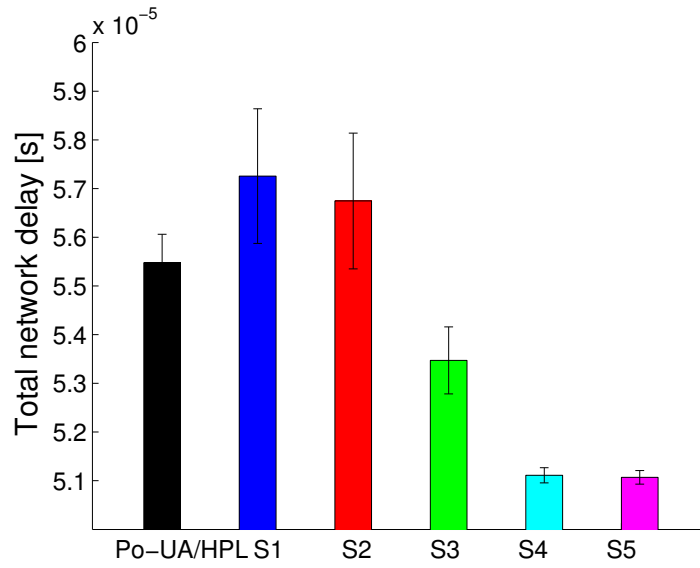


Figure 6.3: Total network delay for the considered settings and for Po-UA/HPL in LTE scenario for an urban deployment.

computed as follows:

$$100 \times \left(1 - \frac{\text{total network power for the considered setting}}{\text{total network power for Po-UA/HPL model}}\right), \quad (6.33)$$

where the total network power is replaced by the expression of C_p^L in (6.4). Figure 6.2 shows that settings S1 and S2 exhibit the highest percentage of power saving at 3.5%, followed by S3 at 2% and by S4 and S5 at 0.4%. In order to examine the cause of power savings in settings S1, S2 and S3, we provide the percentage of the operation modes of the BSs in Tab. 6.4. S1 has the highest percentages of BSs transmitting at the second power level and in sleep mode, followed by S2 and S3.

Table 6.4: Percentage of the BS operation modes [%]

	First power level	Second power level	Sleep
S1	82	15.33	2.67
S2	82.44	14.89	2.67
S3	88.89	9.78	1.33

Let us investigate the total network delay for the considered settings compared to the Po-UA/HPL model. The total network delay is computed according to the expression of C_d^L given in (6.5). Figure 6.3 shows that S5 has the lowest total network delay, followed successively by

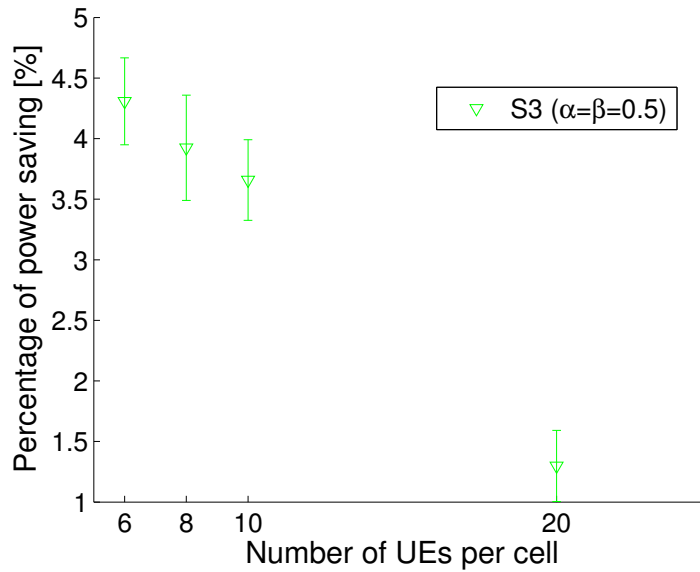


Figure 6.4: Power saving for setting S3 for non-uniform UEs distribution in LTE scenario for an urban deployment.

S4, S3, S2, and S1. Particularly, in S5 preference is given to minimizing the delay ($\beta = 0.99$). As for scenarios with decreasing values of β , more BSs transmit at the second power level or are in sleep mode (as shown in Tab. 6.4). Thus, UEs experience higher delays. Compared with the Po-UA/HPL model, we obtain a reduction in the total network delay that equals 3.6% in S3, while in S4 and S5, the delay reduction equals 8.1%.

6.5.2.2 Non-Uniform Distribution of UEs

In this section, we investigate the case of non-uniform UE distribution on the achievable power saving and delay reduction. In this case, the positioning of the UEs is generated in the cell following a Gaussian distribution centered at the BS positioning with a mean 0 m and a standard deviation of 200 m. The simulated results are plotted as a function of the number of UEs per cell, and we only study the performance of setting S3 ($\alpha = 0.5$, $\beta = 0.5$).

In Fig. 6.4, the percentage of power saving decreases as the number of UEs per cell increases. Precisely, with the increase of the number of UEs per cell, the BS cannot operate at low power level or sleep mode due to the coverage constraints. Moreover, considering the case of six UEs per cell, the percentage of power saving for non-uniform UE distribution (4.3%) is higher than that of the uniform distribution for the same setting S3 (2%, as shown in Fig. 6.2). This is because, in the former case UEs are located near the BS, and the BS can thus lower its transmit power level.

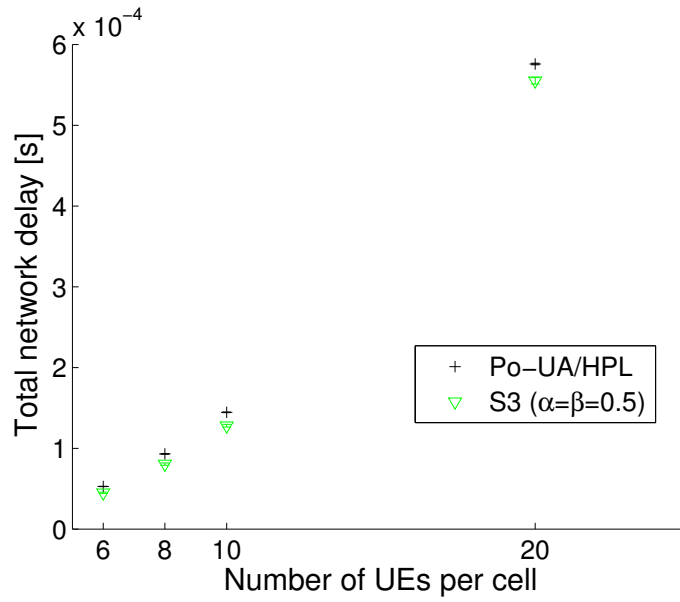


Figure 6.5: Total network delay for setting S3 and for Po-UA/HPL for non-uniform UEs distribution in LTE scenario for an urban deployment.

Fig. 6.5 shows that the total network delay increases as the number of UEs per cell increases. Precisely, the transmission delay of a UE associated with a given BS is proportional to the number of UEs associated with the same BS (as given in (6.2)). Moreover, the obtained total network delay is lower than in the Po-UA/HPL case.

The percentage of power saving for both uniform and non-uniform distributions is relatively low. In fact, the power saving depends on the power consumption of sleep mode and on the power consumption of the second transmit power level. Particularly, the power consumption of sleep mode represents 42% of the power consumption at the highest power level, and the power consumption at the second transmit power level represents 86.7% of the power consumption at the highest level. The aforementioned percentages are relatively high.

6.5.3 Simulation Results in a Rural Deployment

For the rural deployment, we consider an inter-cell distance of 900 m. Moreover, we consider six UEs in each cell, and a total of 54 UEs in the network. The positioning of UEs is generated randomly following a uniform distribution. In this rural deployment, the mean number of covering BSs per UE equals 1.1. The simulation results show that we obtain no power saving for any studied setting. Moreover, we obtain the same average total network delay (5.1439×10^{-5}) for the considered settings, with a negligible delay reduction compared with Po-UA/HPL. Therefore, in rural environments, where UEs are usually covered by one BS, there is no substantial gain

compared with a reference model, and power saving and delay reduction methods are superfluous. Table 6.5 shows the total network delay for the considered settings and for Po-UA/HPL in a rural environment.

Table 6.5: Total network delay [s] for the considered settings and for Po-UA/HPL in a rural environment

Po-UA/HPL	Mean	5.2027×10^{-5}
	95% CI	$[5.186 \times 10^{-5}, 5.218 \times 10^{-5}]$
Settings S1 to S5	Mean	5.1439×10^{-5}
	95% CI	$[5.1357 \times 10^{-5}, 5.1522 \times 10^{-5}]$

6.6 Conclusion

In this chapter, we considered the joint optimization problem of saving power and delay minimization in 4G wireless networks. Thus, we formulated a MILP problem that consists in finding a tradeoff between reducing the network power consumption and selecting the best user association that incurs the lowest transmission delay. Considering an LTE network, different settings reflecting various preferences were studied by tuning the weights of the power and delay objectives. Moreover, we studied the impact of urban and rural deployments on the achievable trade-offs. The power savings mainly depend on user distribution and on the power consumption of the sleep mode. Due to the fact that the power consumption of sleep mode constitutes a large percentage of the power consumption, the power saving is relatively low. Finally, our optimization approach reduces the power consumption of 4% and the transmission delay of 8% when adequately tuned.

In order to solve the MILP problem, we used the branch-and-bound approach. In this approach, the number of integer variables determines the size of the search tree and impacts the computation time of the algorithm. Thus, we noted that our MILP formulation cannot deliver solutions for real size networks. Hence, in the next chapter, we introduce a heuristic algorithm that computes satisfactory solutions for the problem while keeping the computation complexity suitably low for practical implementations.

A Simulated Annealing Heuristic Algorithm for Joint Minimization of Power and Delay in 4G wireless Networks

7.1 Introduction

In the previous chapter, we formulated a MILP problem that jointly minimizes the network power consumption and the transmission delay in broadband wireless networks. In this chapter, we study the case of a realistic LTE network. The challenging issue, which arises in this case, is the high computational complexity necessary to obtain the optimal solution. Therefore, we propose a Simulated Annealing (SA) based heuristic algorithm for the Power-Delay minimization problem [75]. The proposed heuristic aims to compute the transmit power level of the network BSs and associate UEs with these BSs in a way that jointly minimizes the total network power and the total network delay. In order to evaluate the efficiency of the heuristic algorithm for the Power-Delay problem, we compare the results obtained by this heuristic with the optimal solution and the existing solutions. Simulation results show that the proposed algorithm has a low computational complexity which makes it advantageous compared with the optimal solution. Moreover, the heuristic algorithm performs near optimal and outperforms the existing approaches in realistic 4G deployments.

The rest of the chapter is organized as follows. In Section 7.2, we present the Power-Delay minimization problem. In Section 7.3, we present our proposed SA heuristic algorithm. In Sec-

tion 7.4, we present the existing approaches. In Section 7.5, we provide the simulation results. Conclusions are given in Section 7.6.

7.2 Power-Delay Minimization Problem in 4G wireless networks

We introduced the Power-Delay minimization problem in 4G wireless networks in the previous chapter. The considered problem consists of finding the optimal transmit power level of the BSs deployed in the network and optimal user association that minimize the total network cost. The total network cost is defined as the weighted sum of the total network power and the total network delay. The total network power is given by:

$$C_p^L(\Lambda) = \sum_{i \in I, j \in J} N_{TRX}(v\pi_j^L + w_j)\lambda_{i,j}. \quad (7.1)$$

The total network delay is given by:

$$C_d^L(\Lambda, \Theta) = \sum_{i \in I, j \in J, k \in K} \frac{\lambda_{i,j}\theta_{i,k} + \sum_{k'=1, k' \neq k}^{N_u} \lambda_{i,j}\theta_{i,k}\theta_{i,k'}}{\chi_{i,j,k}}. \quad (7.2)$$

The total network cost is thus given by:

$$C_t^L(\Lambda, \Theta) = \alpha C_p^L(\Lambda) + \beta \beta' C_d^L(\Lambda, \Theta). \quad (7.3)$$

Consequently, the objective function of the Weighted-Sum-Power-Delay-Min-LTE problem is given by:

$$\begin{aligned} \underset{\Lambda, \Theta}{\text{minimize}} \quad C_t^L(\Lambda, \Theta) &= \alpha \sum_{i \in I, j \in J} N_{TRX}(v\pi_j^L + w_j)\lambda_{i,j} \\ &+ \sum_{i \in I, j \in J, k \in K} \frac{\lambda_{i,j}\theta_{i,k} + \sum_{k'=1, k' \neq k}^{N_u} \lambda_{i,j}\theta_{i,k}\theta_{i,k'}}{\chi_{i,j,k}}. \end{aligned} \quad (7.4)$$

7.3 A Heuristic Algorithm for the Power-Delay Minimization Problem in 4G wireless networks

Due to the high computational complexity of the Power-Delay minimization problem, we propose a novel SA heuristic algorithm. The proposed heuristic aims at computing the transmit power level of the BSs deployed in the network and associating UEs with these BSs in a way that jointly minimizes the total network power and the total network delay.

The SA algorithm includes an acceptance probability, which can prevent the algorithm from terminating at local minima by allowing hill-climbing moves (*i.e.*, moves which worsen the objective function value) in hopes of finding a global optimum [76, 77]. Moreover, it presents multiple

characteristics suitable to our problem: its ability to scale for large scale optimization problems, and its effectiveness against the exhaustive search.

Our heuristic starts with an initial random feasible solution for both the BS operation modes and user association. Such solution determines the total network cost. Then, at each iteration, a BS is randomly chosen to change its transmit power level which is selected uniformly from the available power levels. For each change of the BS transmit power level, UEs are associated with the best BS according to the Power-Coverage Based User Association (PoCo-UA) (introduced in Section 5.3.2). This is a candidate solution to be used and its total network cost is computed. The candidate solution is accepted as a current solution based on a predefined probability. Typically, the steps are repeated until a given stop criterion is satisfied. The most important parameters controlling the progress of the proposed SA annealing algorithm are: the maximum number of the algorithm's iterations, denoted by $N_{iterations}$. The precision parameter denoted by ϵ , it indicates whether or not the current solution is improved compared with the previous one. Finally, a positive constant denoted by T , which determines the acceptance probability of the candidate solution.

7.3.1 SA Heuristic Algorithm for the Power-Delay-Min Problem

Algorithm 4 describes the different steps of our SA heuristic algorithm for the Power-Delay-Min problem. The algorithm takes as inputs the number of BSs, the number of transmit power levels, the number of UEs in the network, and the initial solution consisting of: an initial random operation mode of the BS Λ^0 , an initial random user association Θ^0 , an initial cost total network cost C_t^0 (Step 1). The algorithm outputs the operation mode of the BSs Λ_{SA} , the user association Θ_{SA} and the total network cost C_{tSA} (Step 18). Let C_t^q denotes the total network cost at iteration q . The algorithm starts with an initial random feasible solution for both BS operation modes and user association. Such solution determines the initial total network cost which is computed according to (7.3). Then, at each iteration, a BS is randomly chosen to change its transmit power level which is selected uniformly from the available power levels (Step 3). Afterwards, the coverage constraint is verified for all UEs in the network (Step 4). If all network UEs are covered then each UE is associated with the active BSs according to PoCo-UA (Step 5), and the total network cost C_t^* is computed according to (7.3) (Step 6). This is a candidate solution to be used. If the difference of the total network cost between the candidate solution and the current solution is negative, the candidate solution is directly taken as the current solution as it improves the total network cost (Step 10). Otherwise, a random variable $\mu \in [0,1]$ is generated uniformly (Step 12). If $\mu \leq e^{-(C_t^* - C_t^{q-1})/T}$ (Step 13), then the candidate solution is accepted as the current solution (Step 14). Typically, the iterations are repeated until a given stop criterion is satisfied. For instance,

Algorithm 4 SA Heuristic Algorithm for the Power-Delay Minimization Problem

```

1: Input:  $N_{bs}, N_l, N_u, \Lambda^0, \Theta^0, C_t^0$ .
2: for  $q = 1$  to  $N_{iterations}$  do
3:   Compute new operation mode of the BS  $\Lambda^*$ ;
4:   if  $\forall k \in K, \exists (i, j) \in (I, J) / \chi_{i,j,k} \lambda_{i,j}^* \geq \chi_{threshold}$  then
5:     Compute the new user association  $\Theta^*$  according to PoCo-UA;
6:     Compute  $C_t^*$  according to (7.3);
7:     if  $\frac{|C_t^* - C_t^{q-1}|}{C_t^{q-1}} < \epsilon$  then
8:       break;
9:     else if  $C_t^* - C_t^{q-1} \leq 0$  then
10:       $C_t^q = C_t^*, \Lambda^q = \Lambda^*, \Theta^q = \Theta^*$ ;
11:    else if  $C_t^* - C_t^{q-1} > 0$  then
12:      Draw a uniform random variable  $\mu \in [0, 1]$ 
13:      if  $\mu \leq e^{-(C_t^* - C_t^{q-1})/T}$  then
14:         $C_t^q = C_t^*, \Lambda^q = \Lambda^*, \Theta^q = \Theta^*$ ;
15:      end if
16:    end if
17:  end if
18: end for
19:  $C_{tSA}^{qSA} = \min_{q=\{1, \dots, N_{iterations}\}} C_t^q$ ;
20:  $\Lambda_{SA} = \Lambda^{qSA}, \Theta_{SA} = \Theta^{qSA}$ .
21: Output:  $\Lambda_{SA}, \Theta_{SA}, C_{tSA}$ .

```

a maximum number of iterations has been exceeded (Step 2) or no more improvement in terms of total network cost can be achieved (Step 7). Once the stopping criteria is met, the algorithm outputs the operation mode of the BSs Λ_{SA} and the user association Θ_{SA} of the iteration q^{SA} that has the minimal total network cost C_{tSA}^{qSA} (Steps 16, 17 and 18).

7.3.1.1 Power-Coverage Based User Association (PoCo-UA)

The Power-Coverage Based User Association is the heuristic introduced in Section 5.3.2 in Chapter 5 for the challenging user association problem. We recall in Algorithm 5 the different steps of PoCo-UA. In PoCo-UA, the probability that a UE is associated with a given BS is proportional to the peak rate perceived by this UE and inversely proportional to the number of UEs covered by the

Algorithm 5 Power-Coverage based User Association

```

1: Input:  $\Psi_k, c(\psi), \psi \in \Psi_k$ .
2: Initialize  $\Delta_k = \emptyset$ ;
3: for  $k \in K$  do
4:   if  $|\Psi_k| \neq 1$  then
5:     for  $\psi \in \Psi_k$  do
6:       Compute  $r_k^\psi = \frac{\chi_{\psi,j,k}}{\sum_{\psi \in \Psi_k} \chi_{\psi,j,k}}, \rho_\psi^k = \frac{c(\psi)}{\sum_{\psi \in \Psi_k} c(\psi)}$ ;
7:       Compute  $\delta_{\psi,k} = \frac{r_k^\psi / \rho_\psi^k}{\sum_{\psi \in \Psi_k} r_k^\psi / \rho_\psi^k}$ ;
8:        $\Delta_k \leftarrow \Delta_k \cup \{\delta_{\psi,k}\}$ ;
9:     end for
10:     $\psi_k^* = \text{Random}(\Psi_k, \Delta_k) \Rightarrow \theta_{PoCo-UA} = \theta_{\psi_k^*,k} = 1$ ;
11:   else
12:     $\psi_k^* = \{\Psi_k\} \Rightarrow \theta_{PoCo-UA} = \theta_{\psi_k^*,k} = 1$ ;
13:   end if
14: end for
15: Output:  $\Theta_{PoCo-UA}$ ;
```

corresponding BS. Thus, the higher the perceived peak rate from the BS and the lower the number of covered UEs by the BS are, the higher will be the UE probability to be associated to this BS. The PoCo-UA algorithm takes as inputs the set of BSs covering UE k denoted by Ψ_k , and the number of UEs covered by BS ψ denoted by $c(\psi)$ (Step 1). It outputs the user association denoted by $\Theta_{PoCo-UA}$ (Step 15). For UEs covered by several BSs (Step 4), the algorithm proceeds as follows: each UE k computes two coefficients r_k^ψ and ρ_ψ^k for each of its covering BS $\psi \in \Psi_k$ (Step 6). These coefficients take into consideration the peak rate perceived by the UE from the covering BS and the number of UEs covered by this BS, respectively. We combine these coefficients with a probability function in such a way that the probability to be associated with a given BS is proportional to the peak rate perceived by the UE and inversely proportional to the number of UEs covered by the corresponding BS. The probability for UE k to be associated with BS ψ is given by $\delta_{\psi,k}$ (Step 7). $\delta_{\psi,k}$ is added to the set of probabilities of UE k to be associated with its covering BSs, denoted by Δ_k (Step 8). Finally, UE k will be associated with the randomly drawn ψ_k^* according to these probabilities (Step 10).

The complexity of executing PoCo-UA algorithm is in $\mathcal{O}(N_u \times |\Psi_k| \log |\Psi_k|)$. Further, the complexity of executing the heuristic algorithm for the power-delay minimization problem (Algorithm 4) corresponds to the complexity of executing PoCo-UA at each change of the transmit

power level for each BS. Hence, the complexity of Algorithm 4 is in:

$$\mathcal{O}(N_u \times |\Psi_k| \log |\Psi_k| \times N_{iterations}). \quad (7.5)$$

7.4 Existing Approaches

In this chapter, we consider the two existing approaches introduced in Section 5.4 in Chapter 5. The first approach is Po-UA/HPL which is based on legacy cellular networks where BSs transmit at a fixed power level and UEs are associated with the BS delivering the highest SNR [27]. In Po-UA/HPL, we assume that all BSs transmit at the highest power level. In this case, all UEs are thus covered by at least one BS and they are associated with the BS delivering the highest SNR.

The second approach is based on the existing approaches that consists in minimizing the total network power while ensuring the coverage constraint for all network UEs. It also considers the power adjustment capability of the BS as in our approach. $\rho_{i,j,k}$ denotes the parameter indicating whether UE k is covered by BS i transmitting at power level j . Thus, this approach can be formulated as the following optimization problem (\mathcal{P}_2):

$$\underset{\Lambda}{\text{minimize}} \quad C_p^L(\Lambda) \quad (7.6)$$

$$\text{subject to:} \quad \sum_{j \in J} \lambda_{i,j} = 1, \quad \forall i \in I, \quad (7.7)$$

$$\begin{aligned} \sum_{i \in I, j \in J} \rho_{i,j,k} \lambda_{i,j} &\geq 1, \quad \forall k \in K, \\ \lambda_{i,j} &\in \{0, 1\}, \quad \forall i \in I, \forall j \in J. \end{aligned} \quad (7.8)$$

Constraints (7.7) state that every BS transmits only at one power level. Constraints (7.8) ensure that a given UE covered by at least one BS. Solving problem (\mathcal{P}_2) provides the operation mode of the network BSs. Then, UEs are associated with the BS delivering the highest SNR. This approach is denoted by Po-UA/Min-Po.

For both approaches, the total network power, the total network delay, and the total network cost are computed according to (7.1), (7.2) and (7.3), respectively.

7.5 Performance Evaluation

7.5.1 Evaluation Method

In order to study the efficiency of the proposed heuristic algorithm for the Power-Delay minimization problem in 4G wireless networks, we implement this algorithm in MATLAB [66] on

IGRIDA¹ [78]. We compare its solution with the optimal one and the existing solutions Po-UA/HPL and Po-UA/Min-Po. In order to compute the optimal solution of the Weighted-Sum-Power-Delay-Min-LTE problem, we resort to the MILP formulation. Therefore, we solve the MILP Weighted-Sum-Power-Delay-Min-LTE problem and (\mathcal{P}_2) problem using the branch-and-bound method with the CPLEX solver [73]. We consider a realistic positioning of the 4G network BS for the district 14 of Paris in France [79]. The network topology is composed of 18 cells ($N_{bs} = 18$) and the positioning of UEs follows a random uniform distribution, as shown in Fig. 7.1.

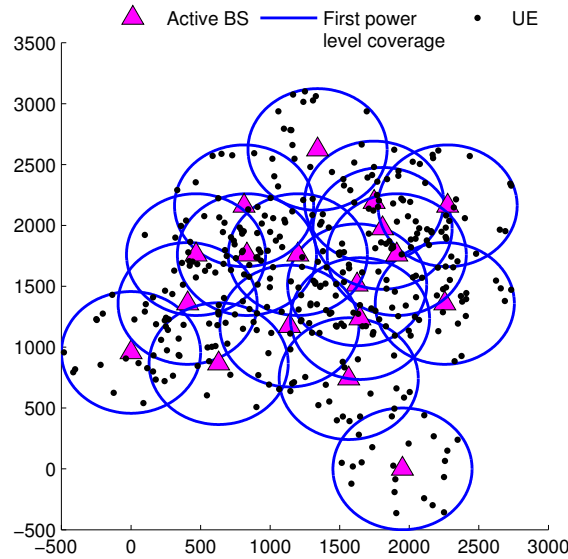


Figure 7.1: 4G network topology of the district 14 of Paris.

In the BS power model, we set for simplicity the number of transmit power levels to three ($N_l = 3$). Precisely, an active BS is able to transmit at two different power levels, and when the power level equals three, the BS is in sleep mode. In the previous chapter, we noted that the power savings mainly depend on the power consumption of the sleep mode. Thus, in this chapter, we consider that when the BS is in sleep mode, it consumes only power due to signal processing. In [63], it is estimated that the power consumption of signal processing circuits accounts for only 10% of the total consumed power. Therefore, in this chapter, we assume that in sleep mode, the BS power consumption is negligible. As in the previous chapter, we consider that the BSs are transmitting using omni-directional antennas. The simulated LTE system bandwidth is 5 MHz, therefore we have 25 RBs available in each cell. We Assuming a frequency reuse 3 scheme in the network to mitigate the inter-cell interference, 8 RBs are thus available in each cell. The fair-time sharing model is used, and the scheduler allocates periodically all RBs to each UE at each

1. IGRIDA is a computing grid available to research teams at IRISA/INRIA, in Rennes. It is designed to provide an easy to use platform for code development as well as an efficient computing facility for production runs.

Table 7.1: Simulation parameters for LTE

Parameter	Value
N_{bs}	18
N_l	3
Input parameters of power consumption model	$N_{TRX} = 1, v = 4.7, w_1 = w_2 = 130 \text{ W}, w_3 = 0 \text{ W}$
Transmit power	$\pi_1 = 10 \text{ W}, \pi_2 = 5 \text{ W}, \pi_3 = 0$
Average power consumed per BS i	$p_{i,1} = 177 \text{ W}, p_{i,2} = 153.5 \text{ W}, p_{i,3} = 0 \text{ W}$
Transmit antenna gain (G_T)	15 dBi
Receiver antenna gain (G_R)	0
Coverage radius for the first and the second power levels	$R_1 = 500 \text{ m}$ $R_2 = 250 \text{ m}$
Environment	Urban
Pathloss model	Cost 231 extended Hata model
Shadowing standard deviation	10 dB
Carrier frequency	2000 MHz
Bandwidth	5 MHz
Frequency Reuse scheme	3
Number of RB per cell	8
Bandwidth per RB	180 KHz
Traffic model	Full buffer
Noise Figure	9 dB
Thermal Noise Density	-174 dBm/Hz
Thermal Noise Power (Th_{NP})	-103.4 dBm

scheduling epoch as explained in Section 6.2.1. Moreover, we assume a full buffer traffic model. The simulation parameters and the pathloss model follow those in [74, 3, 1], which are summarized in Tab. 7.1.

The pathloss between the BS and the UE is computed according to the Cost 231 extended Hata model considering an urban environment [3], with a carrier frequency f of 2000 MHz. The shadowing is represented by a random variable following normal distribution with a mean of 0 dB and a standard deviation of 10 dB. The peak rate computation is performed following the method provided in Section 6.5.1.2 in the previous chapter. This methods take into account the LTE downlink spectral efficiency provided in 3GPP TR 36.942 [3] and the fair-time sharing scheme.

Table 7.2: Percentage of cost reduction for the SA heuristic compared with other solutions [%].

Number of UEs per cell		6	8	10	20
Optimal	Mean	0.75	1.01	1.02	-
Po-UA/HPL	Mean	36.63	30.48	24.58	24.78
	95% CI	[35.34, 37.93]	[29.51, 31.46]	[23.86, 25.30]	[24.36, 25.20]
Po-UA/Min-Po	Mean	33.73	22.05	10.07	10.35
	95% CI	[32.07, 35.39]	[20.76, 23.33]	[9.03, 11.11]	[9.33, 11.37]

We only consider the case where $\alpha = \beta = 0.5$ in (7.4). This balances the tradeoff between minimizing power and delay. The normalization factor β' is calculated in such a way to scale the total network power and the total network delay. In the SA heuristic algorithm, we take the solution provided by (P_2) as the initial operation mode of the network BSs, and the initial user associated is computed according to PoCo-UA (Algorithm 5). Moreover, we take $N_{iterations} = 10^3$, $\epsilon = 10^{-4}$, and $T = 0.1$, and explain later these choices. In each iteration of the SA heuristic algorithm, we run the PoCo-UA user association 10 times and select the best $\theta_{PoCo-UA}$ that gives the minimal total network delay. For the results of the SA heuristic, Po-UA/HPL and Po-UA/Min-Po approaches, we adopt the Monte Carlo method by generating 50 snapshots with different random uniform UE distribution. After computing all the snapshots, we provide the 95% Confidence Interval (CI) for each simulation result. For the results of the MILP problem, we generate only two snapshots and provide the average values. This is due to the large scale test scenario, the memory space limitation and the high computational complexity of the joint Power-Delay-Min problem. For the same reason, we also set a bound limit of 1200 s on the running time in the CPLEX optimization tool. This provides the best solution found within a given number of branch-and-bound iterations. It also provides the gap-to-optimality metric which expresses the gap between the obtained solution and the optimal solution estimated by the solver.

7.5.2 Simulation Results

Let us start by examining the cost reduction that is achieved by the SA heuristic compared with other solutions. The cost reduction is defined as follows:

$$100 \times \left(1 - \frac{\text{total network cost for the SA heuristic}}{\text{total network cost for the considered solution}}\right), \quad (7.9)$$

Recall that the total network cost is the sum of the total network power and the total network delay. Table 7.2 shows the percentage of cost reduction for the SA heuristic compared with other

solutions while varying the number of UEs per cell. On the one hand, results show that the proposed heuristic performs very close to the optimal solution for a small number of UEs per cell (*i.e.*, less or equal 10). Moreover, the heuristic has low computational complexity whereas the optimal solution cannot be computed due to memory space limitation, for a high number of UEs per cell (*i.e.*, larger than 20). It is worth mentioning that the average gap-to-optimality, provided by the CPLEX solver, is 25.64%, 26.34% and 21.05% for 6, 8 and 10 UEs per cell, respectively. This explains why, the SA heuristic provides a small positive cost reduction compared to the optimal solution. On the other hand, results shows that the SA heuristic outperforms Po-UA/HPL with a cost reduction between 24.58 % and 36.63 % for all the considered number of UEs per cell. In fact, Po-UA/HPL does not take into consideration neither saving power, nor minimizing the delay. Since in this approach all BSs transmit at the highest power level, and UEs are associated according to Po-UA, Po-UA/HPL has the highest total network cost for a given number of UEs per cell. Thus, the highest cost reduction is for the SA heuristic compared with Po-UA/HPL for a given number of UEs per cell. Moreover, the SA heuristic also outperforms Po-UA/Min-Po with a cost reduction between 10.07% and 33.73% for all the considered number of UEs per cell. Precisely, in Po-UA/Min-Po, the aim is to minimize only the total network power which is one component of the total network cost and ensure coverage for all UEs in the network. Thus, Po-UA/Min-Po does not take into account the delay minimization. However, in the SA heuristic, the aim is to minimize simultaneously the total network power and the total network delay.

Table 7.3: Percentage of power saving [%] and delay reduction [%] for SA heuristic compared with Po-UA/HPL and Po-UA/Min-Po for 20 UEs per cell.

(a) Power saving			(b) Delay reduction		
Po-UA/HPL	Mean	18.28	Po-UA/HPL	Mean	32
	95% CI	[17.08, 19.48]		95% CI	[30.24, 33.74]
Po-UA/Min-Po	Mean	-17.07	Po-UA/Min-Po	Mean	31.53
	95% CI	[-18.99, -15.15]		95% CI	[29.24, 33.81]

We consider the case where we have 20 UEs per cell, and we show in Tab. 7.3 the power saving and the delay reduction that are achieved by the SA solution compared with Po-UA/HPL and Po-UA/Min-Po solutions. The power saving is computed as follows:

$$100 \times \left(1 - \frac{\text{total network power for the SA heuristic}}{\text{total network power for the considered solution}}\right), \quad (7.10)$$

and the delay reduction is given by:

$$100 \times \left(1 - \frac{\text{total network delay for the SA heuristic}}{\text{total network delay for the considered solution}}\right). \quad (7.11)$$

Compared with Po-UA/HPL, the results show that the SA heuristic provides power saving of up to 18.28 % and delay reduction of up to 32 %. The cause of power saving in the SA heuristic comes from switching-off some BSs and adjusting the transmit power of others. Moreover, the cause of delay reduction is that the SA heuristic associate UEs with the network BS in such a way to minimize the total network delay. Therefore, Po-UA/HPL which is equivalent to legacy networks waste the power without enhancing the delay. In comparison with Po-UA/Min-Po, the power increase is 17.07% while the delay reduction is up to 31.53 %. Precisely, in Po-UA/Min-Po the percentage of switched-off BS is 29.56 % and the percentage of BS transmitting at low power level is 4.22 %. However, in the SA heuristic, the former equals 16.11 % and the latter equals 16.33 %. Moreover, with a high percentage of switched-off BS, the total network delay increases. Therefore, approach Po-UA/Min-Po minimizes the total network power at the detriment of total network delay increase. Consequently, minimizing only the total network power while ensuring covering for UEs in the network, can no longer be considered alone. Further, the SA heuristic balances the tradeoff between minimizing the power and delay.

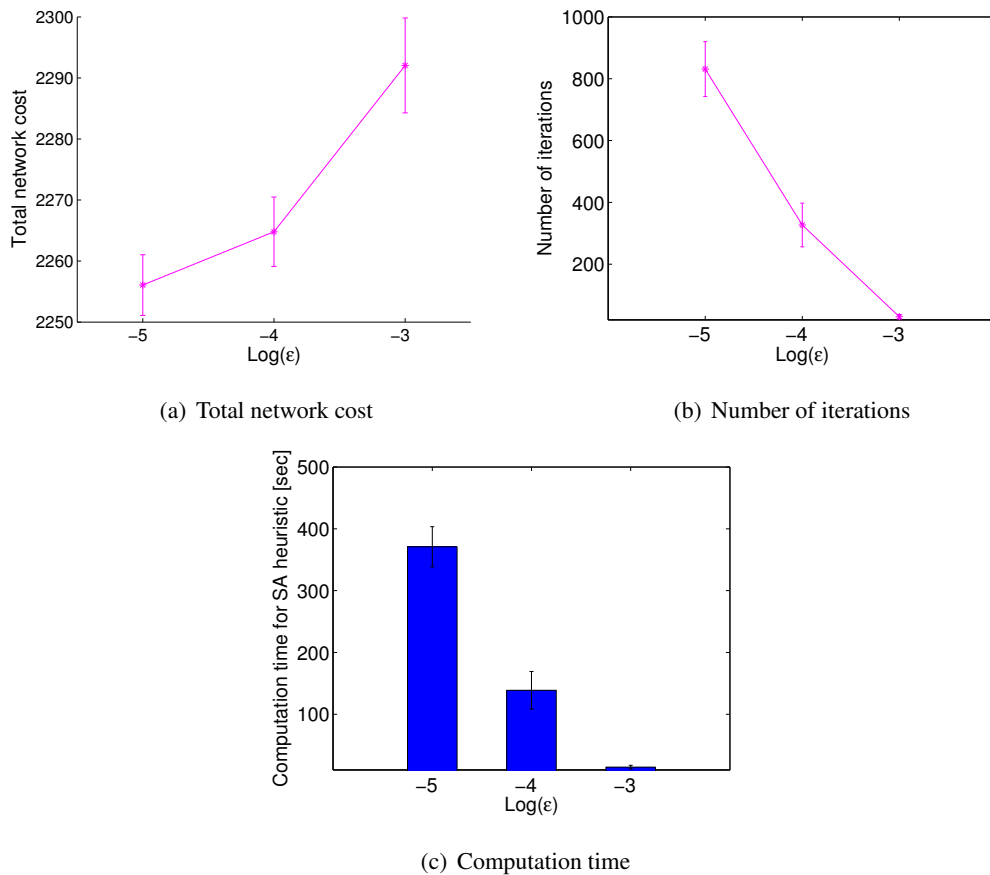


Figure 7.2: SA heuristic results with variation of the precision parameter for 20 UEs per cell.

We now investigate the impact of the controlling parameters of the proposed SA heuristic on the provided solution. Considering the case where we have 20 UEs per cell, we vary the value of

the precision parameter in the SA heuristic algorithm. We plot in Fig. 7.2 the total network cost, the number of iterations of the heuristic algorithm and its computation time as a function of the log of the precision parameter. Figure 7.2(a) shows that we obtain the lowest total network cost for the lowest simulated value of ϵ (*i.e.*, 10^{-5}), and as ϵ decreases the total network cost decreases. Moreover, Fig. 7.2(b) shows that with small values of ϵ , the number of algorithm's iterations increases. This also increases the computation time of the algorithm as shown in Fig. 7.2(c). In the simulations, we choose $\epsilon = 10^{-4}$ providing solutions near to the optimal one with a very moderate time and number of iterations.

7.6 Conclusion

In this chapter, we proposed a novel SA based heuristic algorithm for joint Power-Delay minimization problem in broadband wireless networks. Our goal was to come-up with a large-scale heuristic that has low computational complexity and that reduces the total network cost. We evaluated the SA algorithm on a realistic 4G network in Paris in France. The simulation results showed that the proposed heuristic performs close to the optimal and outperforms existing approaches in terms of cost reduction. Moreover, for large number of UEs in the network, the optimal solution is intractable whereas the heuristic algorithm provides efficient results in a reasonable time. Compared with legacy solutions, the proposed heuristic provides power saving of up to 18% and delay reduction of up to 32%. Thus, it balances the tradeoff between minimizing the power and delay.

Conclusions and Perspectives

The growing energy demands, the increasing depletion of traditional energy resources, together with the surge in mobile internet traffic, all call for green solutions to address the challenge of energy-efficient wireless access networks. This thesis investigates the challenging problem of power saving and transmission delay minimization in wireless networks. Precisely, the aim is to find the best achievable tradeoff between reducing the number of active BSs and adjusting the transmit power of those that remain active while selecting the best user association that incurs the lowest UE transmission delays.

The first step toward achieving this goal is to study the existing approaches that have been considered in the literature to improve the energy efficiency of wireless access networks. Thus, in Chapter 2, we provide an overview on the relevant research in green wireless networks. We classify the latest activities according to different approaches that run at different timescales. We start with the planning and deployment approaches. Then, we present studies on the cell sizing approach coupled with the user association approach. Finally, we put forward the scheduling approach. The contributions of this thesis consist in coming up with novel schemes that implement the strengths of existing approaches to provide power saving, and fill the gap in the literature by also considering the minimization of the transmission delay. In Chapter 3, we formulate the multi-objective optimization problem with aims of minimizing the network power consumption and transmission delay. After exploring typical multi-objective approaches, we resort to the weighted sum method, which enables us to efficiently tune the impact of the power and delay objectives.

We cover two different wireless networks because of their relevance and widespread: IEEE 802.11 WLANs and cellular networks with LTE. In IEEE 802.11 WLANs, we consider a fair-rate sharing scheme because it is the resource sharing model that stems from the Carrier Sense Multiple Access (CSMA) protocol. This resource sharing policy ensures utilitarian fairness, which means

that all UEs have the same share of the overall system capacity, leading to equal rates. In LTE networks, we consider a fair-time sharing scheme as it corresponds to the widely used OFDMA in LTE with a round robin scheduler. This resource sharing policy ensures temporal fairness, meaning that all UEs statistically get a similar number of time slots.

The first part of this thesis addresses the joint power-delay minimization problem in WLANs. Starting from a binary non-linear formulation of the problem, we formulate the Power-Delay minimization problem as a Mixed Integer Linear Programming problem. We study various preference settings that enable to assess the tradeoff between power and delay minimization. We compare our approach with the most frequently deployed WLANs where BSs transmit at a fixed transmit power level while users are associated with the BS delivering the highest signal to noise ratio. When adequately tuned, the proposed optimization approach shows significant power saving and delay reduction compared with legacy solutions. Moreover, our optimization results revealed the impact of the network topology, particularly the inter-cell distance, on both objectives. An interesting conclusion is driven from our analysis: minimizing the power consumption while minimizing the transmission delay does not lead to maximizing the network energy efficiency.

Due to computational complexity issues, we propose a greedy heuristic algorithm for the Power-Delay minimization problem. The extensive simulation results show that the proposed heuristic gives comparable power savings with respect to the optimal and existing solution. Moreover, in dense scenarios, the optimal solution is intractable whereas the heuristic algorithm provides efficient results in a reasonable time.

In the second part of the thesis, we focus on the power-delay tradeoffs in 4G wireless networks. We formulate the power-delay minimization in 4G networks as non-linear problem. Then, we transform it to a MILP problem making it computationally tractable. We consider rural and urban deployments, and assess the impact of the UE's position in the cell on the achievable tradeoffs. We study different settings reflecting various preferences by tuning the weights of the power and delay objectives. The simulation results show that our optimization approach reduces efficiently the power consumption and the transmission delay compared with legacy networks. The power savings mainly depend on UE distribution and on the power consumption in sleep mode.

We study the case of a realistic LTE network. The challenging issue, which arises in this case, is the high computational complexity necessary to obtain the optimal solution. Therefore, we propose a simulated annealing based heuristic algorithm for the joint power-delay minimization problem. The proposed SA heuristic has a low computational complexity and overcomes the scalability issues. We show that the proposed heuristic performs near optimal and outperforms existing approaches in terms of cost reduction. For large number of UEs in the network, the optimal solution is intractable whereas the heuristic algorithm provides efficient results in a reasonable

time. Compared with legacy solutions, the proposed heuristic provides significant power saving and delay reduction.

In this thesis, we assume the existence of a central entity (CE) that has complete control of the network state and elements (such as UEs and BSs). This entity can be easily introduced to the current wireless access networks [21]. The CE is a virtual entity in the network, which can be either implemented in the gateway or distributed in the BSs. The CE senses the network state information such as channel conditions, UEs peak rate, etc. The sensing process can be realized by specific control messages. After collecting the necessary informations, the CE computes the optimal/heuristic solution of the joint Power-Delay minimization problem. Then, the CE diffuses to the network BS their corresponding operation mode. Moreover, it forces the UEs to be associated with the appropriate BS. In LTE-Advanced, the central entity takes decisions on behalf of a group of BSs using Coordinated MultiPoint (CoMP) transmissions, more details on CoMP deployments consideration can be found in [80]. In 802.11 WLANs, the central entity is called Wireless LAN controller, which manages a group of Access Points (APs) called lightweight APs [81, 61]. Lightweight Access Point Protocol (LWAPP) is a draft Internet Engineering Task Force (IETF) standard, authored by Cisco Systems, that standardizes the communications protocol between lightweight access points and WLAN controllers [82].

In practice, in WLANs, the UEs rely on the beacon frame (sent at least every 100 ms) to evaluate their performances (through their received signal power level) and hence their peak rate. In LTE, UEs measure the channel quality based on pilots, i.e. Cell Specific Reference Signals (CRS) that are spread across the whole band. The peak rate can be easily inferred from the evaluated channel quality.

After the work discussed throughout this thesis, some topics are worth to be investigated. We have identified some aspects for further study that we will describe in the following. A very interesting perspective is to consider various traffic types. For instance, we consider not only elastic traffic but also streaming traffic. Streaming traffic is produced by real-time applications such as video streaming, gaming and VoIP. The major requirement of such traffic is bounded delay. Therefore, we can model this type of traffic in our problem by adding constraints on the transmission delay for UEs with streaming sessions. Let $K_1 \subset K$ denote the set of UEs with elastic sessions and $K_2 \subset K$ denote the set of UEs with streaming sessions. The power-delay minimization problem with traffic differentiation is thus given by:

$$\begin{aligned} & \underset{\Lambda, \Theta}{\text{minimize}} && C_t(\Lambda, \Theta) = \alpha C_p(\Lambda) + \beta \beta' C_d(\Lambda, \Theta), \end{aligned} \quad (8.1)$$

$$\text{subject to: } (3.1) \text{ to } (3.7).$$

$$T_{i,j,k} \lambda_{i,j} \theta_{i,k} \leq \eta, \quad \forall i \in I, \forall j \in J, \forall k \in K_2. \quad (8.2)$$

Constraints 8.2 ensure that the transmission delay of UEs with streaming sessions does not exceed η which is a value determined by the application's type.

Further, we can assign a high priority for UEs with streaming sessions by adding high weighting coefficients to the corresponding delays. The total network delay can thus be given by:

$$C_d(\Lambda, \Theta) = \nu_1 \sum_{i \in I, j \in J, k \in K_1} T_{i,j,k} \cdot \lambda_{i,j} \cdot \theta_{i,k} + \nu_2 \sum_{i \in I, j \in J, k \in K_2} T_{i,j,k} \cdot \lambda_{i,j} \cdot \theta_{i,k}, \quad (8.3)$$

where ν_1 and ν_2 are the weighting coefficients representing the relative priority of the two traffic types. With $\nu_2 \gg \nu_1$, more importance is given to minimizing the delay of UEs with streaming sessions.

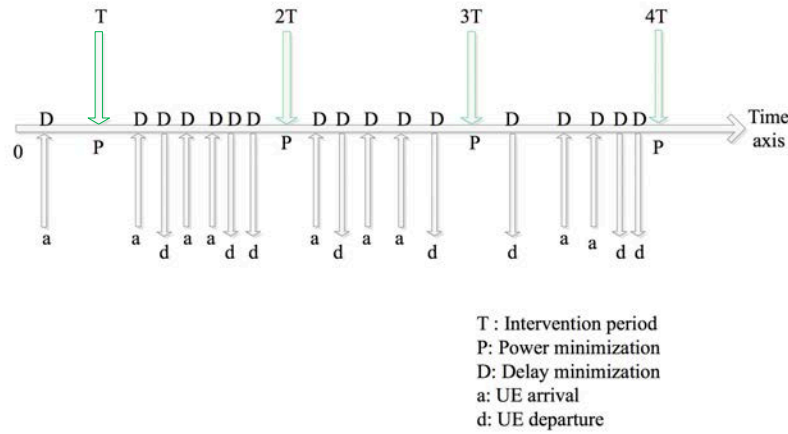


Figure 8.1: Power-delay minimization in a dynamic scenario [4].

Another interesting perspective is to study the dynamics of the network and its impact on power saving and delay minimization. In particular, taking into consideration the mobility of UEs, the arrival and departure of the UEs in the network. Since the timescale of arrival and departure of UEs in the network and the corresponding user association process is smaller than the period on which the operation mode of the network BSs are determined, decisions can not take place upon UEs arrivals and departures. Upon the classification provided in Chapter 1, the operation mode of the BSs which goes under the cell sizing approaches is performed at medium timescales (*e.g.*, hours). This timescale is similar to the order of mid-term traffic-pattern [24]. While, the user association is performed at small temporal levels (*e.g.*, typically less than minutes). Therefore, we can decompose the power-delay minimization into two sub-problems, in which the BS operation problem is solved at a larger timescale than the user association problem. The first sub-problem consists in minimizing the total network power while ensuring the coverage constraint for all

network UEs. We assume the existence of a central server that intervenes at regular time intervals (periodic intervention). It provides the operation mode of the network BSs either optimally or heuristically. Then, at each UE arrival or departure, UEs are associated with the network BSs in a way that minimizes the total network delay. The user association problem is solved also either optimally or heuristically [23, 22]. Figure 8.1 illustrates the proposed approach for solving the power-delay minimization in a dynamic scenario.

Finally, an interesting perspective is to study the power delay minimization problem in heterogeneous networks. Precisely, studying the case of macro LTE base stations integrated with WLAN access points located in different hotspots is a very promising approach. The objective is to investigate means of minimizing the network power consumption and transmission delay by offloading UEs from cellular networks to WLANs [83]. As a matter of fact, WLANs have always been an attractive solution for catering the increasing data demand in mobile networks because of the high bit rates they provide, the simplicity in deployment and maintenance, and the lower CAPEX they insure [84].

A

List of Publications

A.1 International conferences with peer review

1. Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, A Heuristic Algorithm for Joint Power-Delay Minimization in Green Wireless Access Networks, in *International Conference on Computing, Networking and Communications (ICNC), Workshop on Computing, Networking and Communications (CNC)*, Anaheim, USA, 2015.
2. Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, Joint Power-Delay Minimization in 4G Wireless Networks, in *Wireless Days*, Rio de Janeiro, Brazil, 2014.
3. Farah Moety, Samer Lahoud, Kinda Khawam and Bernard Cousin, Joint Power-Delay Minimization in Green Wireless Access Networks, *IEEE Personal, Indoor and mobile radio Communications (IEEE PIMRC)*, London, United-Kingdom, 2013.
4. Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, Power-Delay Tradeoffs in Green Wireless Access Networks, in *Vehicular Technology Conference (VTC FALL 2013)*, Las Vegas, USA, 2013.
5. Farah Moety, Marc Ibrahim, Samer Lahoud and Kinda Khawam, Distributed Heuristic Algorithms for RAT Selection in Wireless Heterogeneous Networks, in *IEEE Wireless Communications and Networking Conference: Mobile and Wireless Networks (IEEE WCNC)*, Paris, France, 2012.

A.2 Submitted Publications

- Farah Moety, Samer Lahoud, Bernard Cousin and Kinda Khawam, Optimization Models for the Joint Power-Delay Minimization Problem in Green Wireless Access Networks, *submitted to Computer Networks*, 2014.

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