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THÈSE

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*Opportunistic spectrum usage and optimal
control in heterogeneous wireless networks*

par

Mohammed RAISS EL FENNI

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Abstract

The present dissertation deals with how to use the precious wireless resources that are normally wasted by under-utilization of networks. We have been particularly interested to all resources that can be used in an opportunistic fashion using different technologies. We have designed new schemes for better and more efficient use of wireless systems by providing mathematical frameworks. In this sense, the rest of this dissertation is divided into three parts: The cognitive radio, delay tolerant networks and ad-hoc networks.

In the first part, We have been interested in cognitive radio networks, where a cellular service provider can lease a part of its resources to secondary users or virtual providers. Indeed, in one hand we have studied how we can increase the service time of a secondary user in a cognitive radio network. Knowing that primary users have priority among other users all the time, we have proposed two schemes that enhance the QoS of secondary users and manage their handoff. The performance improvement gained by applying such schemes to multiple wireless service providers have been investigated. In the other hand, we were interested to how a virtual provider can determines the optimal amount of bandwidth he has to lease from the spectrum owner. The objective is to design a scheme that achieves an optimal solution for the virtual operator with respect to users strategies. Furthermore, we have elaborated a decision theoretic approach when the provider has partial/complete information on the system state.

In the second part, we have chosen delay-tolerant networks as a solution to reduce the pressure on the cell traffic, where mobile users come to use available resources effectively and with a cheaper cost. We have focused on optimal strategy for smartphones in hybrid wireless networks. While using mobile phones, users are subject to fees and consume energy from their limited batteries. Based on the utility of the last message received, users decide whether to activate the mobile device, and if so, which technology to use (WiFi or 3G). We have shown how to cope with such a tradeoff, by devising aging control policies. The goal of an aging control policy is to provide high quality of service while reducing energy consumption and 3G usages, by leveraging WiFi connectivity when available. Whereas the reduction in energy consumption is of interest mainly to subscribers, the

reduction in 3G usages is of interest both to service providers and subscribers. We have proved the existence of an optimal strategy in the class of threshold strategies, wherein users activate their mobile devices if the age of their messages surpasses a given threshold and remain inactive otherwise. Furthermore, we have extended the previous model to a more general case that models the availability of an access point by a Markov process. Indeed, users are not based only on the age of their messages to take actions, but also on the availability of access points. We have shown many properties of the optimal policy, and accuracy of our model has been validated against traces from real world.

In the last part, an alternative to delay-tolerant networks, specially in regions that are not covered by the cellular network, is to use Ad-hoc networks. Indeed, they can be used as an extension of the coverage area. We have developed a new analytical modeling of the IEEE 802.11e DCF/EDCF. We have investigated the intricate interactions among layers by building a general cross-layered framework to represent multi-hop ad hoc networks with asymmetric topology and traffic. The model predicts the throughput of each connection as well as the stability of forwarding queues at intermediate nodes. Finally, we have shown how to take benefit from the interaction between NETWORK, MAC and PHY layers.

Résumé et organisation de la Thèse

Durant cette thèse nous nous sommes intéressés à une meilleure façon d'utiliser la précieuse bande passante, qui est normalement gaspillée à cause de la sous-utilisation des réseaux sans fil. Nous nous sommes particulièrement intéressés à toutes les ressources qui peuvent être utilisées de façon opportuniste en utilisant différentes technologies. Nous avons conçu de nouveaux modèles pour une utilisation meilleure et plus efficace des systèmes sans fil. Dans ce sens, le reste de cette thèse est divisé en trois parties.

Dans la première partie, nous nous sommes focalisés sur les réseaux de communication cognitifs, où un fournisseur de service cellulaire peut louer une partie de ses ressources à des utilisateurs secondaires ou à des fournisseurs virtuels. En effet, d'une part, nous avons étudié comment on peut augmenter le temps de service d'un utilisateur secondaire dans un réseau radio cognitif. Sachant que les principaux utilisateurs sont prioritaires parmi tous les autres utilisateurs tout le temps, nous avons proposé deux schémas qui améliorent la qualité de service des utilisateurs secondaires et gèrent leur transfert. Nous avons étudié l'amélioration de la performance acquise par l'application de ces régimes à plusieurs fournisseurs de services sans fil. D'autre part, nous étions intéressés à la façon dont un fournisseur virtuel peut déterminer la quantité optimale de bande passante qu'il doit louer auprès du propriétaire du spectre. Nous avons eu pour objectif de concevoir un système qui permet d'obtenir une solution optimale pour l'opérateur virtuel par rapport aux stratégies des utilisateurs, la gestion de la bande passante et certains critères d'équité. Une approche théorique de décision lorsque le fournisseur a une connaissance partielle et complète de l'état du système a été élaborée.

Dans la deuxième partie, nous nous sommes intéressés à l'augmentation importante de la charge de trafic dans le réseau cellulaire. En effet, les gens actuellement utilisent de plus en plus leurs téléphones mobiles pour accéder à Internet (e-mails, agenda, réseaux sociaux...), ce qui nous a motivé à utiliser les réseaux tolérant au délai comme une deuxième solution pour réduire la pression sur le réseau cellulaire. Dans ce cas, les utilisateurs

mobiles peuvent être utilisés efficacement les ressources disponibles avec un coût moins élevé. Nous nous sommes concentrés sur les stratégies optimales pour smartphones dans les réseaux hybrides sans fil. Tout en utilisant les téléphones mobiles, les utilisateurs sont soumis à des frais et consomment de l'énergie. Basé sur l'utilité de la dernière mise à jour effectuée, les utilisateurs décident d'activer ou pas leurs appareils mobiles, et choisissent quelle technologie utiliser (WiFi ou 3G). Nous montrons comment faire face à un tel compromis, en concevant des politiques contre le vieillissement de l'information. L'objectif d'une telle politique est de fournir une haute qualité de service tout en réduisant la consommation d'énergie et les utilisations de la 3G, en tirant parti de la connectivité Wi-Fi lorsqu'elle est disponible. En outre, nous étendons le modèle précédent à un cas plus général où la disponibilité d'un point d'accès est modélisée par un processus de Markov. En effet, les utilisateurs ne se basent plus uniquement sur l'âge de leurs messages, mais aussi sur la disponibilité des points d'accès. Une alternative aux réseaux tolérant au délai, en particulier dans les régions qui ne sont pas couvertes par le réseau cellulaire, est d'utiliser les réseaux ad-hoc. En effet, ils peuvent être utilisés comme une extension de la zone de couverture.

Nous avons développé dans la dernière partie, une nouvelle modélisation analytique du protocole IEEE 802.11e. Nous avons étudiés les interactions complexes entre les couches en construisant une architecture protocolaire communicante de type inter-couches, pour représenter les réseaux ad hoc multi-sauts ayant une topologie et un trafic asymétriques. Le modèle prédit le débit de chaque connexion, ainsi que la stabilité de la transmission des files d'attente au niveau de noeuds intermédiaires. Enfin, nous avons montré comment bénéficier de l'interaction entre la couche Réseau, MAC et Physique.

Les principales contributions et les grandes lignes de chaque partie sont énumérées ci-dessous

1^{ère} Partie: Amélioration de la qualité de service dans les réseaux radio cognitifs. La radio cognitive est une technologie émergente en matière d'accès sans fil, qui vise à améliorer considérablement le spectre radio bidirectionnelle. Nous étudions l'amélioration de la performance et la réutilisabilité des canaux par l'application de la radio cognitive à un système constitué de plusieurs fournisseurs de services sans fil. Nous considérons deux types d'utilisateurs: les primaires et les secondaires. Deux systèmes d'accès basés sur la priorité sont proposés pour les utilisateurs secondaires afin de mieux gérer leur transfert de données. Ces deux régimes sont différents dans le sens où l'un d'eux permet à chaque fournisseur d'accès de donner plus de priorité à ses propres utilisateurs de type cognitifs en interrompant le service des usagers avec faible priorité, tandis que l'autre ne le permet pas. Le système est modélisé par un processus de Markov, avec un temps continu et un espace d'états fini. En raison du nombre très important

d'états, nous proposons aussi une méthode robuste pour approcher le vecteur de distribution de probabilité stationnaire de ce processus de Markov. Sur la base de cette approximation, nous développons plusieurs indicateurs de performance pour les deux types d'utilisateurs. Les résultats numériques montrent que cette approximation est très proche de la solution exacte. Enfin, nous montrons que l'utilisation du spectre des utilisateurs cognitifs augmente avec le schéma de priorité proposé, en particulier pour un moyen et fort trafic. Le propriétaire du spectre peut aussi louer une partie de sa bande passante à un opérateur virtuel. Ce dernier pour éviter tout gaspillage de ressources (notamment d'argent), doit optimiser sa réservation de canaux. Nous étudions dans ce sens la maximisation des revenus dans un système sans fil où les utilisateurs intéressés partagent un spectre commun et interfèrent les uns avec les autres. La capacité est augmentée en proportion du nombre d'utilisateurs. Notre objectif est de concevoir un système qui permet d'obtenir une solution optimale pour l'opérateur virtuel en tenant compte de la stratégie des utilisateurs et la gestion de la bande passante. Nous considérons une tarification forfaitaire pour les utilisateurs. Deux cas sont étudiés: d'une part, une approximation au problème initial lorsque le fournisseur a une parfaite connaissance de l'état de canal de chaque utilisateur, et d'autre part, une approche théorique basée sur un POMDP est élaborée lorsque le fournisseur ne dispose que d'informations partielles sur l'état du système.

2^{eme} Partie: Contrôle optimal dans les réseaux tolérant au délai. La demande pour les services Internet qui exigent des fréquentes mises à jour par le biais de petits messages, a considérablement augmenté au cours des dernières années. Bien que l'utilisation de ces applications par les utilisateurs domestiques est généralement gratuite, l'accès à partir d'appareils mobiles est soumis à des frais et consomme de l'énergie. Si un utilisateur active son dispositif mobile et est à portée d'un prestataire de services, une mise à jour du contenu est reçue au détriment des différents coûts. Nous concevons des politiques de lutte contre le vieillissement. Une politique de contrôle du vieillissement consiste à décider, en fonction de l'utilité actuelle du dernier message reçu, d'activer le dispositif mobile ou non, et si oui, quelle technologie utiliser (WiFi ou 3G)? Nous montrons l'existence d'une stratégie optimale dans la classe des stratégies avec seuil, dans laquelle les utilisateurs activent leurs appareils mobiles si l'âge de leurs messages dépasse un seuil donné, sinon ils restent inactif. L'analyse s'étend à de multiples utilisateurs où les fournisseurs de contenu offrent des bonus en terme de prix pour les utilisateurs, afin de les inciter à télécharger les mises à jour. Nous montrons que ce jeu a un équilibre de Nash dans lequel tous les utilisateurs jouent des stratégies mixtes. Nos résultats sont obtenus en utilisant des techniques de programmation dynamique, et la précision de notre modèle est validée par rapport à des traces réelles du réseau de bus UMass DieselNet.

3^{eme} Partie: Les interactions entre couches du IEEE 802.11e basé sur un réseau ad hoc multi-sauts. Les performances de la norme IEEE 802.11 dans les réseaux sans fil multi-sauts dépendent des caractéristiques du protocole lui-même, et celles des différentes couches. Nous considérons l'utilisation d'un réseau ad-hoc comme une alternative ou une extension d'un réseau cellulaire. Les utilisateurs peuvent bénéficier ainsi d'un meilleur débit surtout dans des régions denses ou à fort trafic. Nous étudions les interactions complexes entre les couches PHY, MAC et réseau du protocole 802.11. Par exemple, nous avons conjointement incorporé le seuil de détection de porteuse, la puissance d'émission, la fenêtre de contention, le nombre de retransmissions maximal par paquet, les taux multiples, les protocoles de routage et la topologie du réseau. Nous avons développé un modèle analytique qui prédit le débit de chaque connexion ainsi que la stabilité de la transmission des files d'attente au niveau des nœuds intermédiaires. La performance d'un tel système a été également évaluée par simulation. Nous avons montré que les mesures de performance de la couche MAC sont affectées par l'intensité du trafic qui va être transféré. Plus précisément, le taux des tentatives d'envoi et la probabilité de collision dépendent du flux du trafic, la topologie et du routage.

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For/Dedicated to/To my...

Chapter 1

Introduction

1.1 Introduction and Motivation

The development of wireless and mobile technologies has revolutionized the world of telecommunications, causing an explosive growth of the Internet. Such technologies are evolving towards broadband information access across multiple networking platforms. Broadband wireless access systems include many technologies, recent ones are Wireless Local Area Networks (WLAN), Wireless Personal Area Networks (WPAN), as well as the widely used mobile access technologies, such as General Packet Radio Service (GPRS), Wide Code Division Multiple Access (WCDMA), Enhanced Data rate for Global Evolution (EDGE), 3G communications systems, and recently the called 4G technologies like the Worldwide Interoperability for Microwave Access (WIMAX) and Long Term Evolution (LTE).

Complementing each other is one of the characteristics of these wireless access technologies. Indeed, wide coverage areas, full mobility and roaming are the principle advantages of cellular networks and 3G, but traditionally offer low bandwidth connectivity and limited support for data traffic. On the other hand, WLANs provide high data rate at low cost, but only within a limited area. Whereas WIMAX for instance, can supply mobile broadband for anyone, anywhere and whatever the technology and the access mode.

In order to provide mobile users with the requested multimedia services and corresponding Quality of Service (QoS) requirements, these radio access technologies, will be integrated to form a heterogeneous wireless access network. Such a network will consist of a number of wireless networks, as illustrated in figure 1.1, and will form the next-generation of wireless networks.

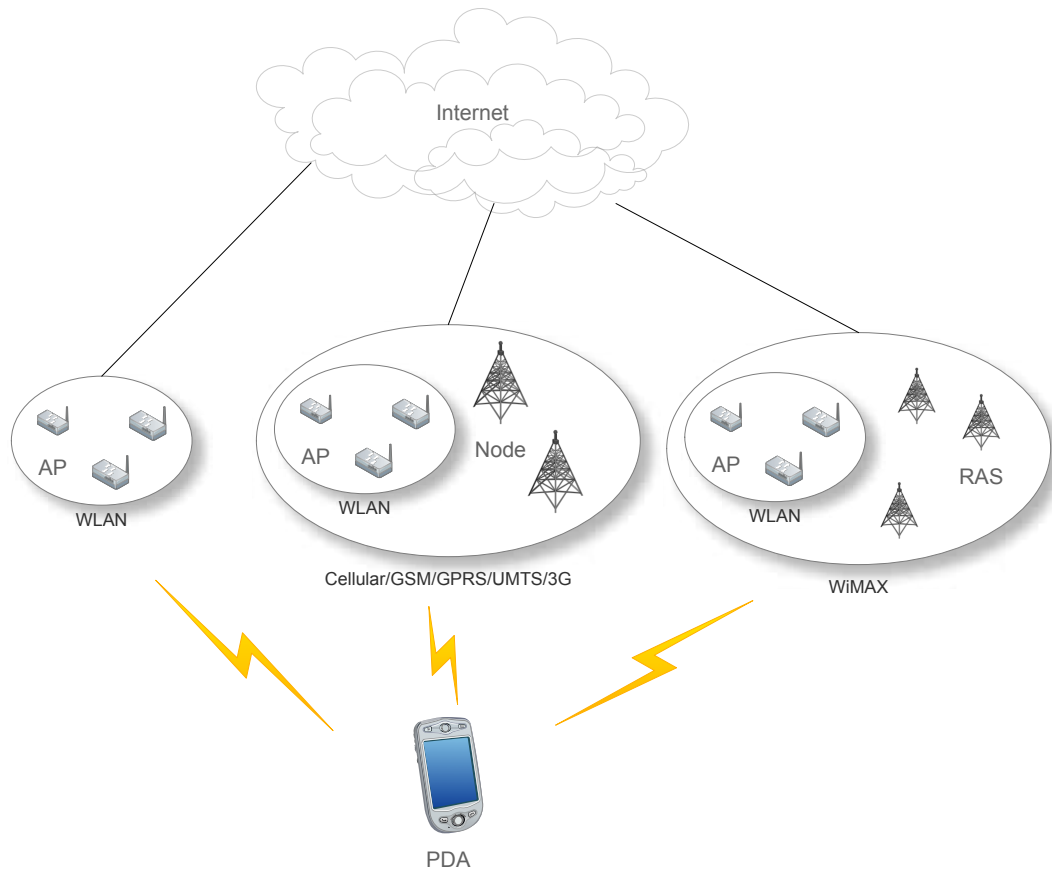


FIGURE 1.1: Integration of heterogeneous wireless access networks

In terms of mobile technology and its subscribers, there has been a clear shift from fixed to mobile cellular telephony, especially since the turn of the century. By the end of 2010, there were over four times more mobile cellular subscriptions than fixed telephone lines [1]. This continued dramatic increase in demand for all types of wireless services (voice and data) are fueling the demand for large increases in capacity, data rates, and supported services (e.g., multimedia services). Indeed, service providers around the world are feeling the strain as tremendous growth in mobile data traffic swamps their networks, and the spectrum scarcity is becoming a severe problem that we have to face.

This rapid expansion of wireless services is an indication that significant value is placed on accessibility and portability as key features of telecommunication [2]. Indeed, wireless devices have maximum utility when they can be used anywhere at anytime. One of the greatest limitations to that goal, however, is finite power supply. Since batteries provide limited power, a general constraint of wireless communication is the short continuous operation time of mobile terminals. Therefore, power management is one of the most challenging problems in wireless communication, and many research has addressed this topic [3],[4],[5],[6],[7],[8].

The network control mechanism determines the access control and the traffic forwarding decisions in order to accomplish certain objectives. The quantitative performance objectives should reflect the requirements posed by applications. Various objectives have been considered and studied in various works including the overall throughput, power optimization, utility optimization of the allocated rates as well as optimization of general objective functions.

There are many ways that can be used by service providers to deal with those issues. Indeed, load balancing, network selection, resource allocation, admission control, fast and efficient vertical handoff mechanisms, and provisioning of QoS on an end-to-end basis are some of the major research issues related to the development of heterogeneous wireless access networks. This dissertation covers different aspects of analysis, design, and optimization of protocols and architectures for heterogeneous wireless access networks. In particular, we are interested to optimize the use of the precious wireless resources that are normally wasted by under-utilization of networks. we are particularly interested to all resources that can be used in an opportunistic fashion using different technologies. In a cognitive radio network, we design and model a QoS framework that allow to secondary users and virtual providers to maximize their channels use. Whereas in a delay tolerant network, we derive optimal strategies for mobile users in both known and unknown environment. Furthermore, we study optimal spectrum utilization in multi-hop ad hoc wireless networks.

1.2 Techniques for design of QoS-based models: general overview

In this section we give an overview of technologies that interest us. We introduce the cognitive radio technology, delay tolerant networks, IEEE 802.11 DCF and some basic theoretical concepts, which will be used in the chapters of this dissertation.

1.2.1 Cognitive radio architecture

Cognitive radio (CR) is a critical part of many future radio systems and networks. Some regulatory domains, such as the Federal Communications Commission (FCC) in the United States are already considering the use of CR technologies. The term cognitive radio was first used publicly in an article by Joseph Mitola III, where it was defined as [9]:

"The point in which wireless personal digital assistants (PDAs) and the related networks

are sufficiently computationally intelligent about radio resources and related computer-to-computer communications to detect user communications needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs.”

A radio system having the 'cognition' capability is called a CR, which generally uses the Software defined Radio (SDR) technology. The level of cognition attributed to a radio depends on the complexity and intelligence of its cognitive engine, which can have learning capabilities and make decisions based on real-time changes in the operating conditions of the radio. Today, the term cognitive radio generally refers to a radio system that has the ability to sense its radio frequency environment and modify its spectrum usage based on what it detects.

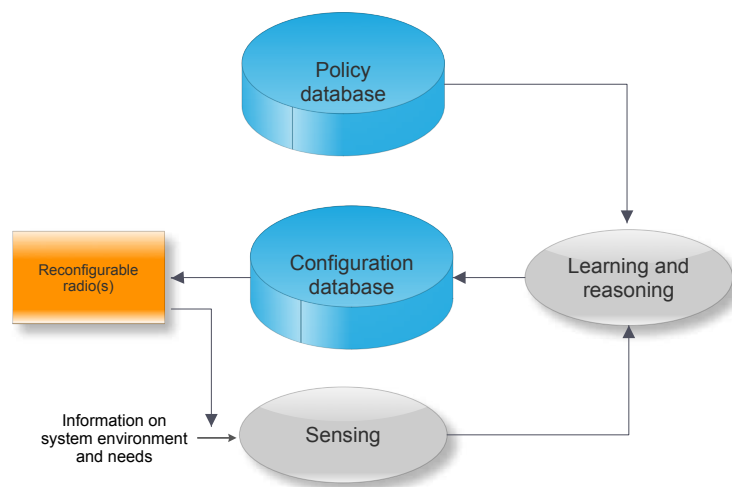


FIGURE 1.2: The components that exist in a cognitive radio system

Figure 1.2 provides a high-level view of the components that can be found in a cognitive radio system. The different components are defined as follows:

- Reconfigurable radio component: Minimally, there must be at least one reconfigurable radio component with parameters, such as operating frequency and bandwidth, although many more parameters may exist.
- A sensing engine must exist that may accept inputs from the radio components, but many other sources also can be present, such as other networked nodes or data sources on the Internet and data such as geolocation data.
- A policy database that defines the spectrum access strategy based on knowledge of the spectrum utilization. The optimal decision depends on the PUs' behavior, as well as the competitive or cooperative behavior of SUs. Different techniques,

such as optimization theory, game theory and stochastic optimization, can be used in order to obtain an optimal solution.

- A reasoning engine that accepts inputs from the sensing engine and a policy database and determines an appropriate configuration for the radio components. The reasoning engine can be capable of learning, based on experience.
- A configuration database that would maintain the current configuration of the radio components. A simple CR system might have a single reconfigurable radio component accepting sensing information from a single local node and no external data sources.

The CR technology is used in order to face the spectrum scarcity problem. Indeed, it allows unlicensed users to access the spectrum as long as they do not harm the licensed ones, which can be achieved by spectrum sensing or power control. With the development of the CR technology, dynamic spectrum sharing (DSS) and opportunistic spectrum access (OSA) become promising approaches that achieve major gains in the efficiency of spectrum utilization. In the first approach, secondary users are allowed to use simultaneously the spectrum with the primary ones, as long as their transmissions do not cause harmful interferences. In OSA approach, unlicensed users access licensed channels only when primary users are not using them.

1.2.2 Delay tolerant network

Having a continuous network connectivity is not always a simple task. Indeed, networks operating in mobile or extreme terrestrial environments, or planned networks in space, lack this continuous connectivity. Delay-tolerant networking (DTN) seeks to address that issue in heterogeneous networks (see Figure 1.3). A delay-tolerant network is a network designed to operate effectively over extreme distances. In such an environment, long latency sometimes measured in hours or days is inevitable. However, similar problems can also occur over more modest distances when interference is extreme or network resources are severely overburdened.

A DTN requires hardware that can store large amounts of data. Such media must be able to survive extended power loss and system restarts. It must also be immediately accessible at any time. Ideal technologies for this purpose include hard drives and high-volume flash memory. The data stored on these media must be organized and prioritized by software that ensures accurate and reliable store-and-forward functionality.

The DTN architecture is conceived to relax most of assumptions built into the Internet protocols, based on a number of design principles that we summarized here [10]:

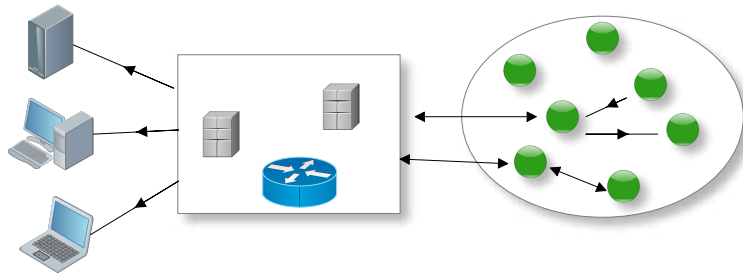


FIGURE 1.3: A Delay tolerant network with heterogenous networks

- It uses variable-length messages as the communication abstraction to help enhance the ability of the network to make good scheduling/path selection decisions when possible.
- It uses a naming syntax that supports a wide range of naming and addressing conventions to enhance interoperability.
- It uses storage within the network to support store-and-forward operation over multiple paths, and over potentially long timescales (i.e., to support operation in environments where no end-to-end paths may ever exist); do not require end-to-end reliability.
- It provides security mechanisms that protect the infrastructure from unauthorized use by discarding traffic as quickly as possible.
- Traffic can be classified in three ways, called expedited, normal and bulk in order of decreasing priority. Expedited packets are always transmitted, reassembled and verified before data of any other class from a given source to a given destination. Normal traffic is sent after all expedited packets have been successfully assembled at their intended destination. Bulk traffic is not dealt with until all packets of other classes from the same source and bound for the same destination have been successfully transmitted and reassembled.

1.2.3 Overview of IEEE 802.11 DCF/EDCF

The distributed coordination function (DCF) of the IEEE 802.11, which is a set of standards for implementing wireless local area networks, is based on the CSMA/CA protocol in which a node starts by sensing the channel before attempting any packet. Then, if the channel is idle it waits for an interval of time, called the Distributed Inter-Frame Space (DIFS), before transmitting. But, if the channel is sensed busy the node

defers its transmission and waits for an idle channel. In addition, to reduce collisions of simultaneous transmissions, the IEEE 802.11 employs a slotted binary exponential back-off where each packet in a given node has to wait for a random number of time slot, called the back-off time, before attempting the channel (Figure 1.4). The back-off time is uniformly chosen from the interval $[0, W - 1]$, where W is the contention window that mainly depends on the number of collisions experienced by the packet. The contention window W is dynamic and given by $W_i = 2^i W_0$, where i represents the stage number (usually, it is considered as the number of collisions or retransmissions) of the packet, and W_0 is the initial contention window. The back-off time is decremented by one slot each time when the channel is sensed idle, while it freezes if it is sensed busy. Finally, when the data is transmitted, the sender has to wait for an acknowledgement (ACK) that would arrive after an interval of time, called the Short Inter-Frame Space (SIFS). If the ACK is not received, the packet is considered lost and a retransmission has to be scheduled. When the number of retransmissions expires, the packet is definitively dropped.

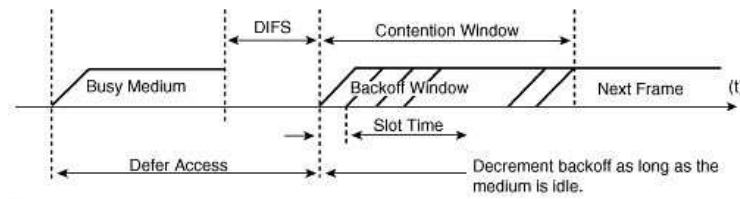


FIGURE 1.4: Contention window mechanism in CSMA/CA protocol

To consider multimedia applications, the IEEE 802.11e uses an enhanced mode of the DCF called the Enhanced DCF (EDCF) which provides differentiated channel access for different flow priorities. In this manner, the delay to access the channel is reduced for those who have a delay constraint. The main idea of EDCF is based on differentiating the back-off parameters of different flows. So, priorities can be distinguished due to different initial contention window, different back-off multiplier or different inter-frame space. An Arbitration IFS (AIFS) is used instead of DIFS. The AIFS can take at least a value of DIFS, then, a high priority flow needs to wait only for DIFS before transmitting to the channel. Whereas a low priority flow waits an AIFS greater than DIFS.

1.2.4 Markov decision processes

In real life, decisions that humans and computers make on all levels usually have two types of impacts: (i) they cost or save time, money, or other resources, or they bring revenues, as well as (ii) they have an impact on the future, by influencing the dynamics.

In many situations, decisions with the largest immediate profit may not be good in view of future events. Markov Decision Processes (MDPs) model this paradigm and provide results on the structure and existence of good policies and on methods for their calculation. In an MDP, the decision maker, usually called agent, makes decisions sequentially, and we denote by decision epoch, every time the agent has to make a decision. At every decision epoch, the agent observes the state of the system and chooses an action. Choosing an action in a given state has mainly two results: the agent receives a reward, and the system evolves to a possibly different state at the next decision epoch. an MDP problem is formulated as follows:

- Decision epochs: Denote by T the set of decision epochs. If this set is finite, the decision problem is said to be finite horizon problem, otherwise it is called an infinite horizon problem.
- States : At every decision epoch, the system occupies a state $s(t)$. S denotes the set of all possible states.
- Actions: We denote the set of actions for each state s by A_s .
- Immediate reward: $r_t(s; a)$, defined for state $s \in S$ and action $a \in A_s$, the real-valued function that assigns, for a given decision epoch t , a value as outcome for taking the action a in the state s . If $r_t(s; a)$ is positive, it is called reward function. Otherwise, it is called cost function.
- Transition probabilities: When the agent takes the action a in the state s , the system state in the next decision epoch is determined by transition probabilities $p_t(\cdot|s; a)$. We usually assume that $\sum_{j \in S} p_t(j|s; a) = 1$.
- Decision rules: Decision rules are functions that specify the action choice when the system is in the state s at the decision epoch t .

A decision rule is said to be Markovian if it depends on previous system states and actions only through the current state of the system, and said to be deterministic if it determines the action to be chosen with certainty. Agents have strategies in a decision problem. We define A policy, or strategy by a sequence of decisions that specifies the decision rule to be used at every decision epoch, and it is expressed by $\pi = (d_1; d_2; \dots)$. We call a stationary policy, a policy that determines the action to be chosen depending on the system state, regardless of decision epochs. A stationary policy has the form $\pi_s = (d; d; \dots)$.

MDP can not model any decision problem, specially the ones with uncertainty about the state of the system. In that case, decision problems under partially observable environment, can be modeled using a POMDP framework.

1.2.5 Partially observable Markov decision processes

Adding partial observability to an MDP is not a trivial addition. Solution procedures for MDPs give values or policies for each state. The use of these solutions requires the state to be completely known at all times and with complete observability. Partial observability clouds the idea of the current state. A POMDP is just an MDP, with only one difference. In a POMDP we add a set of observations to the model. So instead of directly observing the current state, the state gives us an observation which provides a hint about what state it is in. The observations can be probabilistic; so we need to specify also an observation function. This observation function simply tells us the probability of each observation for each state in the model. We can also have the observation likelihood depend on the action if we like. Formally a POMDP is defined as a tuple $(T, S, A, R, P, \Omega, O)$ where

- T, S, A, R and P describe an MDP.
- Ω is the finite set of observations an agent can experience.
- O is the observation function.

As the agent does not directly observe the global state of the system, it infers the global system state based on past observations and actions that can be summarized in a belief vector $\omega(t) = \omega_1(t); \dots; \omega_N(t)$, where $\omega_j(t)$ is the conditional probability that the system state $s(t) = j$, at the time slot t . An exact solution of a POMDP yields the optimal action for each possible belief over the world states.

1.3 Contributions

The chapters of this dissertation are organized in three parts. In the first one, we were interested to cognitive radio networks, where a cellular service provider can lease a part of its resources to secondary users or virtual providers. Indeed, in one hand we studied how we can increase the service time of a secondary user in a cognitive radio network. In the other hand, we were interested to how a virtual provider can determines the optimal amount of bandwidth he has to lease from the spectrum owner. In the second part, one solution to reduce the pressure on the cell traffic is to use delay-tolerant networks, where mobile users come to use available resources effectively and with a cheaper cost. We can also speak about self organized users. We focused on optimal strategies for smartphones in hybrid wireless networks. We shown the existence of an optimal strategy in the class of threshold strategies, wherein users activate their mobile devices if their utility

surpasses a given threshold and remain inactive otherwise. An alternative to delay-tolerant networks, specially in regions that are not covered by cellular networks, is to use Ad-hoc connections. Indeed, it can be used as an extension of the coverage area of a cellular network. We developed in the last part, a new analytical modeling of the IEEE 802.11e DCF/EDCF. We investigated the intricate interactions among layers. The model predicts the throughput of each connection as well as the stability of forwarding queues at intermediate nodes. Our main contributions and the outline of each part are listed below.

Part 1 : Opportunistic Spectrum Access in Cognitive Radio Networks. Cognitive radio is an emerging technology in wireless access, aimed at vastly improving the way radio spectrum is utilized. We investigate the performance improvement gained by applying cognitive radio to a multiple Wireless Service Providers (WSPs). We consider several WSPs and two types of users: primary (licensed) and secondary (unlicensed) users. Two different schemes are proposed for unlicensed users to manage their handoff. These two schemes are different in the sense that one allows to each WSP to give more priority to his own unlicensed users by dropping low priority ones, while the other does not allow that. The system is modeled by a Markov process, with continuous time and finite state space. Due to the very large number of states, we propose a robust method to approximate the stationary probability distribution vector of Markov process. Based on this approximation, we develop several performance metrics, blocking and dropping probabilities for both kinds of unlicensed users. As the service provider allows to secondary users to access its network, he can also allow to a virtual provider to lease some bandwidth. Indeed, we were interested to how a virtual provider can determine the optimal amount of bandwidth he has to lease from the spectrum owner. We had the objective to design a scheme that achieves an optimal solution for the virtual operator with respect to users strategies, bandwidth management and some fairness criteria. We considered a flat rate pricing for users. Two cases are studied: first, an approximation to the original problem when the provider has a perfect knowledge about the channel state of each user. In the second case, a decision theoretic approach based on a POMDP framework was elaborated when the provider has only partial information on the system state.

Part 2 : Optimal Control and Self Organized users in Delay Tolerant Networks. The demand for Internet services that require frequent updates through small messages, such as micro blogging, has tremendously grown in the past few years. Although the use of such applications by domestic users is usually free, their access from mobile devices is subject to fees and consumes energy from limited batteries. If a user activates his mobile device and is in range of a service provider, a content update is received at the expense of monetary and energy costs. We show how to cope with such

a trade off, by devising aging control policies. An aging control policy consists of deciding, based on the current utility of the last message received, whether to activate the mobile device, and if so, which technology to use (WiFi or 3G). We show the existence of an optimal strategy in the class of threshold strategies, wherein users activate their mobile devices if the age of their messages surpasses a given threshold and remain inactive otherwise. The analysis extends to multiple users where the content providers (publishers) offer bonus packages to users, so as to motivate them to download updates. We show that this game has a Nash equilibrium in which all mobile users play mixed threshold strategy. Our results are derived using dynamic programming techniques, and the accuracy of our model is validated against traces from the UMass DieselNet bus network. We extend the previous model to a more realistic one, by considering partial information about WiFi access point availability. We propose an analytical model based on a Partially Observed Markov Decision Process (POMDP) with an average reward criterion. Using this model, we show properties of the optimal aging control policy.

Part 3 : On Modeling Multi-hop Wireless Ad hoc Networks. Performance of IEEE 802.11 in multi-hop wireless networks depends on the characteristics of the protocol itself, and on those of the other layers. We are interested in modeling the IEEE 802.11e Enhanced Distributed Coordination Function. We investigate the intricate interactions among PHY, MAC and Network layers. For instance, we jointly incorporate the carrier sense threshold, the transmit power, the contention window size; the retransmissions retry limit, the multi rates, the routing protocols and the network topology. Then, we build a general cross-layered framework to represent multi-hop ad hoc networks with asymmetric topology and asymmetric traffic. We develop an analytical model that predicts the throughput of each connection as well as the stability of forwarding queues at intermediate nodes. Performance of such a system is also evaluated via simulation. We show that the performance measures of MAC layer are affected by the traffic intensity of flows to be forwarded. More precisely, attempt rate and collision probability are dependent on the traffic flows, topology and routing.

Part I

Opportunistic Spectrum Access in Cognitive Radio Networks

Chapter 2

Quality of service enhancement in cognitive radio networks

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2.1 Introduction

Cognitive radio is a paradigm for wireless communication in which either a WSP or a wireless node changes its transmission or reception parameters to communicate efficiently avoiding interference with licensed or unlicensed users [11]. The term was initially applied to extending software radios with a self awareness about its characteristics and requirements, in order to determine an appropriate radio etiquette to be used [12],[13]. This alteration of parameters is based on the active monitoring of several factors in the external and internal radio environment, such as radio frequency spectrum, user behavior and network state. In a network supporting cognitive radio, secondary users (SUs) opportunistically use the spectrum that is normally assigned to primary users (PUs) but not being used at a particular time and geographic location. Thus, a secondary user must leave the channel once detecting the presence of a licensed user. At the same time, the

SU will scan all other channels and handoff to another unused one if available; otherwise, its communication is interrupted. Once interrupted, the SU can either leave the system or wait in a queue so that its connection is terminated or suspended. Some concerns on unlicensed spectrum usage and performance analysis of cognitive radio networks are discussed in [14]-[15].

In [14], the authors propose a new dynamic spectrum access scheme for cognitive radio wireless networks with and without buffering for secondary users to avoid direct blocking. A Markov model was developed to analyze the proposed spectrum sharing policies. The result indicates that the buffer is able to significantly reduce the SU blocking probability and noncompletion probability with very minor increased forced termination probability. The analytic model has been verified by simulation. A rigorous study of performance in opportunistic spectrum access systems that limit disruptions to unpredictable primary users is presented in [16]. The goal was to understand whether dynamic spectrum access can provide reliable spectrum to secondary users while respecting hard disruption limits that protect primary-user transmissions.

The authors in [17] consider that in a cognitive radio network (CRN), instead of direct leaving, an interrupted secondary user is suspended to wait for accessing another channel in a call level queue. The policy for handling the packets generated by the secondary user during the suspending period can be either delaying or discarding. According to these two packet level policies, the queue is separated into two parts, delay queue and discard queue. The chapter mainly analyzes the performance of a CRN with such a two part call level queue. Other works were interested in economical aspect. In [18] a Stackelberg game between three players; spectrum owner, primary users and secondary users is presented under the opportunistic spectrum access (OSA) model, where the secondary users (followers) share the channel with primary users in time and SUs access is performed through a non perfect listen-before-send scheme. It is shown through simulations that the spectrum owner can enhance its revenue by allowing OSA with a non zero interference probability to the primary users. Virtual unlicensed spectrum is another way to share bands with primary users without interferences. Thus, in [15] a cognitive radio approach for usage of virtual unlicensed spectrum is presented. A vision of a cognitive radio based approach that uses allocated spectrum in an opportunistic manner to create virtual unlicensed bands i.e., bands that are shared with the primary users on a non-interfering basis. Dynamic spectrum management techniques are used to be adopted to immediate local spectrum availability. The authors define the system requirements for this approach, as well as the general architecture and basic physical and link layer functions. In general, there are two basic operation models for SUs: OSA which is also called the spectrum overlay paradigm versus spectrum sharing (SS) or the spectrum underlay paradigm. In the OSA model, the SUs are allowed to transmit

over the band of interest when all the PUs are not transmitting at this band. One essential enabling technique for OSA based SUs is spectrum sensing; where the SUs individually or collaboratively detect active PU transmissions over the band, and decide to transmit if the sensing results indicate that all the PU transmitters are inactive at this band with a high probability. The key operation is spectrum sensing; the interested readers may refer to, e.g., [19–22] for an overview of the state of art results in this area. As a counterpart, the SS model allows the SUs to transmit simultaneously with PUs at the same band even if they are active, provided that the SUs know how to control their resultant interference [23]. For instance, in [24] packet collision probability was considered as the PU protection requirement. Under this requirement, the SU must guarantee that the packet collision probability of a PU packet is less than a certain threshold specified by the PU.

In this chapter we consider a system with multiple Wireless Service Providers (WSPs) where multiple SUs are allowed to access the unused licensed spectrum bands without conflicting with PUs. In order to protect the QoS of PUs, each WSP reserves a number of channels allowed to them. Their access to these channels should not be affected by the SUs. We assume that the SUs are equipped with cognitive radio equipment and are able to detect the presence of the licensed users [25],[26]. In [27], the authors were focused on similar problem by studying the benefits that can be gained by adding cognitive radio capabilities to a system of PUs. They considered the case where all SUs are in the same level of priority. The symmetric case was studied, i.e., the case when all networks in the system have the same capacities and number of channels. Moreover, in their model they did not explicit the interaction between networks (handoff of cognitive calls) in terms of migration rates [28]-[29]. Also, the transition probability matrix and the stationary distribution were solved only based on simulations. In this chapter we consider a general framework that extends all limitation of the above work. Furthermore, we consider the prioritization among SUs while accessing the channel. We distinguished two schemes as follows:

- No priority scheme: The agreement between the WSP and the primary users is to guarantee a certain QoS in term of interferences and availability of channels, like throughput and blocking probability. In order to assure the QoS for the licensed users, the WSP determine a threshold on the number of channels allowed to licensed users and reserves the rest of bandwidth to unlicensed users. Since the SU are capable to detect the presence of the PUs, it is allowed to dynamically access unused channels in the primary user bandwidth. Another alternative for SU, is to handoff to another WSP belonging to the system if it has some available resources. Even if the threshold will restrict the use of some channels to PUs, it

will not affect their QoS. Indeed, the threshold is set by the WSP based on its statistics about the arrival and service time of PUs.

- Priority scheme: In this scheme we introduce the priority among SUs in the above scheme. In particular, we assume that a SU has more priority on its home WSP than other SU belonging to another WSP. However, a foreign SU may be pushed out from a WSP if it is fully occupied and reclaim those resources for its own use.

In practice, there is no reserved bandwidth to SUs, and the threshold defined for PUs is exactly the total number of available channels. Therefore, SUs use only empty channels when the PUs are absent or inactive. This case is covered by our model. The interest of this work is to study the benefit of including such threshold by WSPs in term of performance while insuring a QoS to PUs all the time. Indeed, a user can use licensed channels for real time calls in order to guarantee the desired QoS, while the best effort calls are performed using the unlicensed channels with cognitive equipment. Reducing the total cost of the service could be another reason of such kind of priority.

We called SUs in their home WSP, *own* SUs and for others *foreign* SUs. We define a priority among SUs in each WSP. This priority means that an own SU can drop a foreigner one, under some conditions as described in the next section.

Summing up, the main contributions are :

- We propose a new model to describe and analyze the interaction between WSPs with infrastructure deployed in the same geographical area and cover a shared pool of end users. We model the dynamic system as a Markov chain, and derive the performances of the WSPs under two schemes. Due to very large number of states, we propose a new method based on the fixed point to approximate the stationary distribution. Numerical results show that this approximation is very close to the exact solution.
- Unlike several works, our model introduces the priority among secondary users and addresses the issue of spectrum handoff under prioritized SU calls. The performance of the two schemes are evaluated in term of blocking and dropping probabilities.
- We apply a threshold to PUs while insuring their QoS. We study the impact of this threshold and how it influence the spectrum efficiency. Finally, we perform an extensive numerical analysis to provide insightful results about the spectrum utilization of cognitive users. Results show that the spectrum utilization increases with the proposed schemes especially in high load traffic.

The remainder of the chapter is organized as follows. In Section 2.2, we formulate the problem and describe the system. Section 2.3 develops an analysis model with respect to the no priority case. We propose in Section 2.4 the model that gives more priority to own CR flows than foreign flows in each network. Performance evaluation is presented in Section 2.5 and finally, in Section 2.6, we give some numerical results and end with a concluding summary.

2.2 Problem Formulation and System Description

The system under consideration is a collection of N WSPs with infrastructure deployed in the same geographical area and cover a shared pool of end users (see the Figure 1 with 3 service providers). The WSP i possesses K_i channels, and without loss of generality each user requires the capacity of one channel for the duration of its service in order to fulfill its requirements. We consider three types of users:

- The PUs related to a specific WSP with a guaranteed QoS, dedicated channels and without the possibility to have service in other WSPs.
- The users who choose to split their traffic into two different parts to benefit from the advantages of both licensed and unlicensed channels.
- The last kind is SUs who are not attached to any WSP and sense all channels of the system looking for spectrum holes.

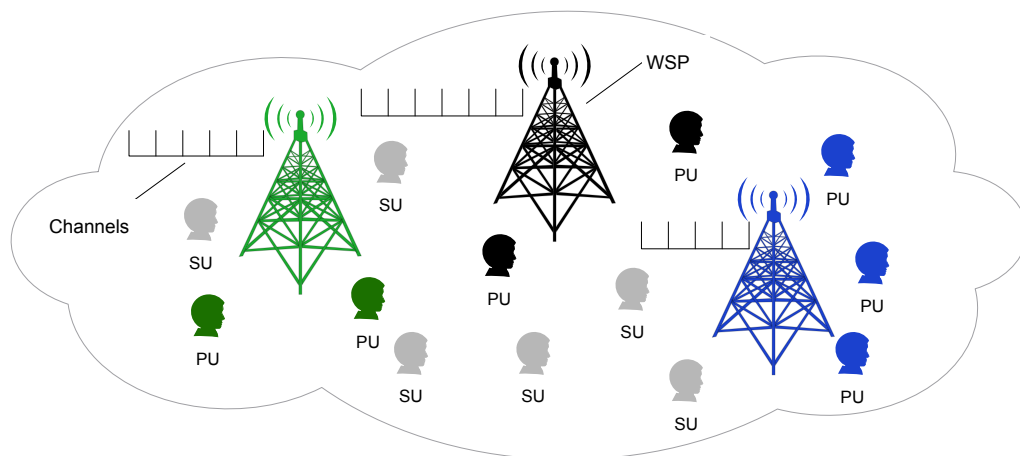


FIGURE 2.1: Illustrative example of a system with three WSPs

A perfect channel is assumed. That is, a channel has two states, it can be either busy or idle. It is also assumed that radio systems always detect radio resource allocations

of each others, here the radio resource refers to bandwidth. We assume that spectral scanning is performed instantaneously, so there is no scanning delay. The offered traffic is modeled with two random processes per radio system. We assume that PUs arrivals of WSP i , follow a Poisson distribution with rate λ_i^{PU} and their service time is exponentially distributed with mean $1/\mu_i^{PU}$. We define $\rho_{PU}^i = \lambda_{PU}^i/\mu_{PU}^i$. Since PUs are not affected by SUs, the probability to have n_{PU}^i PUs in the WSP i is given by

$$q_{n_{PU}}^i = \frac{1}{G} \frac{(\rho_{PU}^i)^{n_{PU}^i}}{n_{PU}^i!}$$

where G is the normalizing constant and n_{PU}^i the number of PUs). Throughout these values, each WSP i is able to estimate the number of licensed channels in order to evaluate the QoS for primary users. However, if the spectrum of WSP i is not fully utilized, the provider may reserve a part of bandwidth for SUs.

The system considered has a total capacity of $M = \sum_{i=1}^N K_i$. However, the WSPs belonging to the system are completely independent of each other, with primary users only being served by their home WSP. As a result, when a WSP reaches its capacity, it must start blocking calls, as it has no available channels. If the WSP has available resources for a primary call, it can accept it. If not, the service is refused and the call ends without having service. Once accepted, a call must have continuous service for the duration of its service time.

Primary and cognitive traffic for WSP i are defined as follows. For cognitive traffic, if resources are not available on its home network, the call can switch to another WSP j ($j \neq i$) with a uniform probability on all WSPs with free resources. As SUs may be

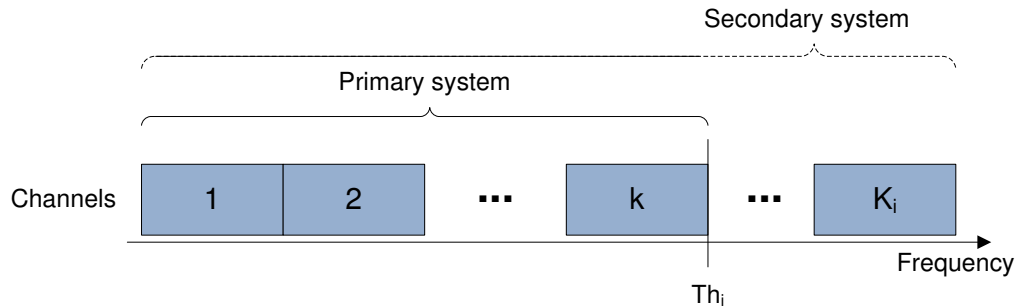


FIGURE 2.2: Channels model of WSP i . The channel k is the last channel allowed to be used by PUs. In the secondary system, the dashed line represents the channels reserved only to SUs, while the other channels could be used by SUs and PUs together.

pushed out from other WPs, an occupancy threshold Th_i for PUs has been included in the model. Figure 2.2 shows the channels model that we used. In WSP i , if the

TABLE 2.1: Main definition parameters

Parameter	Definition
M	Capacity of the system
N	Number of WSPs
K_i	Number of channels in WSP i
Th_i	Threshold of PUs reserved by WSP i
μ_{PU}	Service rate of PUs
μ_{SU}	Service rate of SUs
$\lambda_{new,SU}^i$	Fixed SU arrival rate in WSP i
$\lambda_{out,SU}^i$	External SU arrival rate in WSP i
λ_{PU}^i	PUs arrival rate in WSP i
$\lambda^{j,i}$	Migration rate from WSP j to i
n_{PU}^i	Number of PUs in WSP i
$n(i)$	Total number of users in WSP i
n_{SU}^i	Number of SUs in WSP i
n_{SU}^{-i}	Number of external SUs in WSP i

number of primary users is equal or exceeds the threshold, then new PUs are blocked. The model covers the scenario where PUs have the right to use all channels and SUs take advantage of spectrum only when PUs are absent (particular case). The threshold was included in order to improve the performance of SUs. As PUs have the priority to use the channels, the threshold Th_i doesn't affect the QoS guaranteed by the provider to PUs and their blocking probability depends only on their arrival and service rates. Furthermore, our study propose two schemes : These two schemes are different in the sense that one allows to each WSP to give more priority to his own unlicensed users by dropping low priority users, while the other does not allow that. We summarize the main parameters used in table 2.1.

2.3 Model : No priority scheme

In the no priority scheme there is no priority among SUs in the system. Hence, a SU can be dropped from WSP i only by a PU that request service in a time where all channels reserved to PUs are used. i.e., If 1) a new PU arrives, 2) all channels are occupied, and 3) the number of PUs in the WSP i at that time is strictly lower than the threshold, i.e $n_{PU}^i < Th_i$, where n_{PU}^i is the total number of PUs in WSP i . A primary user is blocked if and only if $n_{PU}^i \geq Th_i$, whereas a SU can not have service in WSP i if $n_{PU}^i + n_{CR}^i = K_i$, where n_{CR}^i is the total number of SUs in WSP i .

2.3.1 System state and transition rates

In order to analyze the behavior of the WSPs, the state of the system at time t is defined by

$$\vec{n}(t) = (n_{PU}^1(t), \dots, n_{PU}^N(t), n_{SU}^1(t), \dots, n_{SU}^N(t)),$$

then, we model the process $\{\vec{n}(t), t > 0\}$ as $2N$ dimensions quasi birth and death Markov chain with continuous time. Let $n(i) = n_{PU}^i + n_{SU}^i$ be the total number of users in WSP i . Thus, we define the space of admissible states as

$$E = \{\vec{n} \in \mathbf{N}^{2N} \mid n(i) \leq K_i; i = 1, \dots, N\}.$$

Let $\lambda_{new,SU}^i$ be the arrival rate of SUs in WSP i (i.e. users splitting their traffic), and let $\lambda_{out,SU}$ be the rate arrival of foreign SUs. We assume that this two rates are characterized by a set of poisson process. Also, we assume that the service time distribution is exponential with μ_{SU}^i . The Poisson process has been found to provide a good representation for arrival calls and service time of a call while Internet traffic exhibits a correlation structure over a wide span of time scales. We will analyze the performance of our schemes in which packets arrivals are modeled by a Markovian arrival which captures the correlation of inter-arrival times among primary users, among secondary users, as well as between the two types of users. These issues are beyond the scope of this study and will be treated in future work. The transition rates from a state \vec{n} to another state \vec{n}' are described as follows. Let \vec{n}_{i+}^c be the state corresponding to a new arrival belonging to class c (PU or SU) and we denote this transition by $q_{\{\vec{n}, \vec{n}_{i+}^c\}}$. Let \vec{n}_{i-}^c be the state when a call from class c ends successfully its service and leaves the system, and we denote this transition by $q_{\{\vec{n}, \vec{n}_{i-}^c\}}$, and let $\vec{n}_{i+,j-}^{c,c'}$ be the state when a new arrival call from class c gives rise to an interrupted call from class c' , and we denote this transition by $q_{\{\vec{n}, \vec{n}_{i+,j-}^{c,c'}\}}$. Then we have

$$\begin{aligned} q_{\{\vec{n}, \vec{n}_{i-}^{PU}\}} &= n_{PU}^i \cdot \mu_{PU}^i, & (2.1) \\ q_{\{\vec{n}, \vec{n}_{i-}^{SU}\}} &= n_{SU}^i \cdot \mu_{SU}^i, \\ q_{\{\vec{n}, \vec{n}_{i+}^{PU}\}} &= \lambda_{PU}^i \cdot \mathbf{1}_{\{n_{PU}^i \neq 0\}}, \\ q_{\{\vec{n}, \vec{n}_{i+}^{SU}\}} &= \lambda_{SU}^i \cdot \mathbf{1}_{\{n_{SU}^i \neq 0\}}, \\ q_{\{\vec{n}, \vec{n}_{i+,j-}^{PU,SU}\}} &= \lambda_{PU}^i. \end{aligned}$$

Now, the transition probability matrix \mathbf{Q} is derived for the process $\{\vec{n}(t), t > 0\}$. The transitions are found for both primary and cognitive calls. The transition probability matrix $\mathbf{Q} = [q_{(\vec{n}, \vec{n}')}]$ can be derived. The steady state vector π ($\pi = \{\pi(\vec{n}), \vec{n} \in E\}$)

of probabilities $\pi(\vec{n})$ can be obtained by resolving the following system:

$$\pi \cdot \mathbf{Q} = \pi \text{ and } \sum_{\vec{n} \in E} \pi(\vec{n}) = 1. \quad (2.2)$$

To solve this problem we propose two different ways, the exact solution, by constructing the matrix Q from all feasible states from the overall system. This solution is complicated and takes a very long time to be solved because of the huge number of states present in the space E . Also, most of the time, a service provider doesn't have complete or enough information about statistics and parameters used by other service providers, like the number of PUs or the threshold reserved for them. In spite of this problem, the authors in [27], solve (2.2) by simulation without taking in account interactions (migration of SU calls) occurring among the WSPs. In this work we present a robust approximation to solve the system of linear equations (2.2), by considering the probability that the total system in state \vec{n} is written as a product of steady state probability of each WSP. In this way we reduce the complexity of the problem and we switch from the study of the space E and the overall system to a smaller space related to each WSP i . The interaction among all these WSPs is studied by considering an approximation to cognitive arrival rate in each WSP. This arrival rate depends on the global state ($\vec{n} \in E$) of the system. Hence, the SU calls arrival rate in the WSP i is given by

$$\lambda_{SU}^i(\vec{n}) = \lambda_{new,SU}^i + \sum_{j \neq i} \lambda_{SU}^{j,i} + \lambda_{out,SU}^i, \quad \text{if } n(i) < K_i, \quad (2.3)$$

where $\lambda_{SU}^{j,i}$ is the SU call migration rate from WSP j to the WSP i ($j \neq i$) and $\lambda_{out,SU}^i$ represents the arrival rate of SUs to WSP i . The arrival rates $\lambda_{SU}^{j,i}$ and $\lambda_{out,SU}^i$ are unknown and depends on the random number of SU calls of the WSP j that go elsewhere. These rates depend on the stationary distribution. We give explicit fixed point method to calculate these arrival rates in the next sub section.

For WSP i , we define the sub state space as follows

$$E_i = \{\vec{n}_i \in \mathbf{N}^2 \mid n(i) \leq K_i; i = 1, \dots, N\},$$

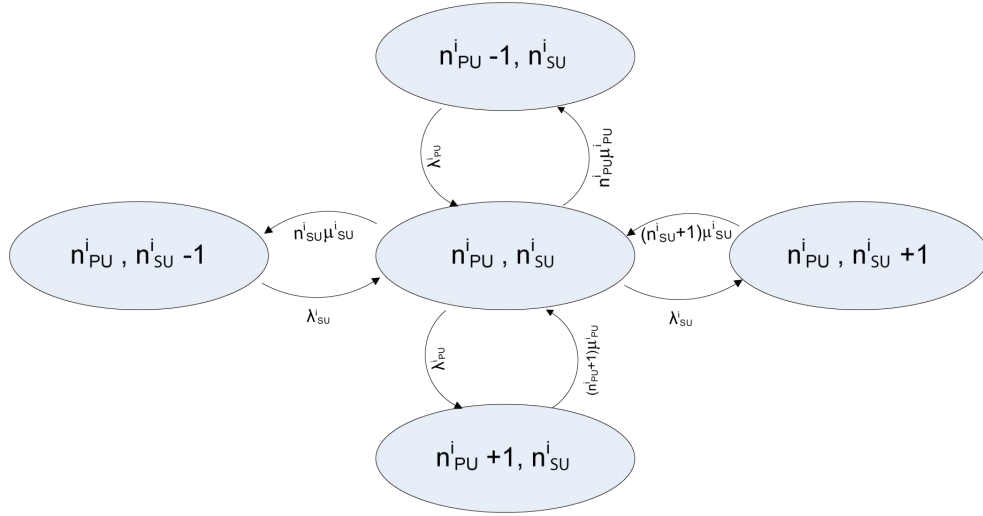
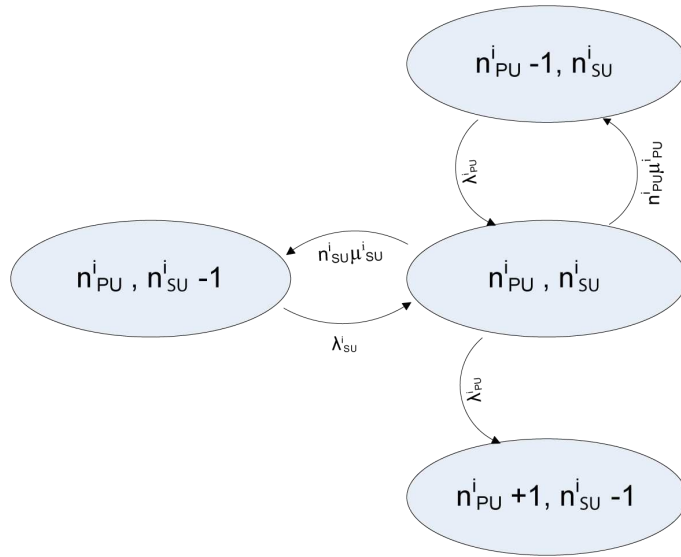
where $\vec{n}_i = (n_{PU}^i, n_{SU}^i)$. The steady state probability of each WSP i is defined by

$$\pi_i = \{\pi_i(\vec{n}_i) \mid \vec{n}_i \in E_i\},$$

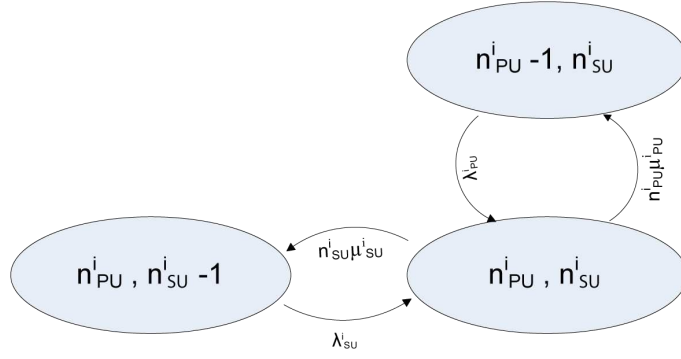
this steady state probability is given by solving the set of balance equations [30]. The different states are described as follows:

1. The states satisfying $n_{PU}^i + n_{SU}^i < K_i$ and $n_{PU}^i < Th_i$ (no saturation case).

2. The states satisfying $n_{PU}^i + n_{SU}^i = K_i$ and $n_{PU}^i < Th_i$, in this case a new PU arrival gives rise to an interrupted SU call.
3. The states satisfying $n_{PU}^i + n_{SU}^i = K_i$ and $n_{PU}^i = Th_i$, here the request of a new PU or SU arrival is refused by the WSP and they are blocked.

FIGURE 2.3: System state transit for $n_{PU}^i + n_{SU}^i < K_i$ and $n_{PU}^i < Th_i$ FIGURE 2.4: System state transit for $n_{PU}^i + n_{SU}^i = K_i$ and $n_{PU}^i < Th_i$

Figures (2.3,2.4,2.5) show the transit rate diagram for network i . On the basis of this latter, we develop the set of global balance equations. In addition, the summation of all steady state probabilities satisfies the normalization constraint $\sum_{\vec{n}_i \in E_i} \pi_i(\vec{n}_i) = 1$. Combining the balance equations, we can solve the steady state probability distribution. Therefore, the transit rate matrix \mathbf{Q}_i and the solution of linear equations $\pi_i = \pi_i \cdot \mathbf{Q}_i$,

FIGURE 2.5: System state transit for $n_{PU}^i + n_{SU}^i = K_i$ and $n_{PU}^i = Th_i$

can be obtained. The set of linear equations can be solved using an iterative method SOR [30].

2.3.2 Calculation of migration rates

in this sub-section we will explicit how to compute the migration rates. A SU call of WSP j go elsewhere if $n(j) = K_j$ (i.e., WSP j uses all of its own resources). Let $a(\vec{n})$ be the number of WSPs that still have resources at the state \vec{n} , then we have

$$a(\vec{n}) = \sum_{i=1}^N \mathbf{1}_{\{n(i) < K_i\}}.$$

The probability ($\pi(\vec{n})$) that the system is in the state \vec{n} , is given by

$$\pi(\vec{n}) = \frac{1}{\alpha} \prod_{i=1}^N \pi_i(\vec{n}_i), \quad (2.4)$$

where $\alpha = \sum_{\vec{n} \in E} \prod_{i=1}^N \pi_i(\vec{n}_i)$. Then, the SU call arrival rate from WSP j to WSP i is given by

$$\lambda_{SU}^{j,i} = \sum_{\vec{n} / n(j) = K_j, n(i) < K_i} \frac{\pi(\vec{n})}{a(\vec{n})} \lambda_{new, SU}^j. \quad (2.5)$$

Also the arrival rate of a cognitive user $\lambda_{out, SU}^i$ is given by

$$\lambda_{out, SU}^i = \sum_{\vec{n} \in E, n(i) < K_i} \frac{\pi(\vec{n})}{a(\vec{n})} \lambda_{out, SU}. \quad (2.6)$$

In order to obtain the arrival rate $\lambda_{SU}^i(\vec{n})$ of SU call arrival to WSP i from (2.3), we first need to compute the SU call arrival rate from j to WSP i ($\lambda_{SU}^{j,i}, j \neq i$). To do

this we follow the Migration rate computing algorithm. With the same way we compute $\lambda_{out,SU}^i$.

Migration rate computing algorithm :

1. Initialize the migration rates by zero in (2.3): $\lambda_{old,SU}^{j,i} = 0$.
2. Calculate the steady state probability $\pi(\vec{n})$ from (2.4).
3. Derive the new values of migration rates from (2.5) and denoted by $\lambda_{new,SU}^{j,i}$.
4. Check the convergence of the migration rates between old and new rates, i.e., if $|\lambda_{new,SU}^{j,i} - \lambda_{old,SU}^{j,i}| < \xi$, where ξ is a very small positive number, then the new migration rates will be used to compute the performance metrics. Otherwise, go to step 2 with the new migration rates as initial values. The iterations are continued until to reach the convergence of rates.

Since the Markov chain has a stationary distribution π , a migration rate $\lambda_{SU}^{j,i}$ exist and can be estimated by the previous Algorithm.

2.4 Model : Priority scheme

Let us in this section make the distinction between own and foreign SUs in a WSP. We give more priority to the users that choose to split their traffic and send a part from it without using their dedicated channels among foreign SUs. This choice of users can be motivated by the nature of their operations (audio call, file transfer...). Based on this priority, if all resources are occupied in his own WSP, a new SU will check if a foreign SU uses one of the channels, and ask for dropping him out. As a result, an SU will not be dropped only by PUs as in the No priority scheme, but also by other SUs if the conditions discussed above are satisfied.

2.4.1 System state and transition rates

As described in the first scheme, we define the system state at time t as follows

$$\vec{n}(t) = (n_{PU}^i(t), n_{SU}^i(t), n_{SU}^{-i}(t), i = 1, \dots, N),$$

where $n_{SU}^{-i}(t)$ is the number of SUs of other WSPs in the WSP i . Then, we model the process $\{\vec{n}(t), t > 0\}$ as $N(N+1)$ dimensions quasi birth and death Markov chain with continuous time and finite state space.

Let $n(i) = n_{PU}^i + n_{SU}^{i,i} + n_{SU}^{-i}$ be the total number of users in WSP i , where $n_{SU}^{i,i}$ represents the number of own SUs. Thus, we define the space of admissible states as follows

$$F = \{\vec{n} \in \mathbf{N}^{N(N+1)} \mid n(i) \leq K_i; i = 1, \dots, N\}.$$

As in the first scheme, arrival and service rates of PUs are characterized by a set of Poisson processes with parameter λ_{PU}^i and an exponential distribution with parameter μ_{PU}^i respectively. We assume that the service time of SUs in WSP i is distributed exponentially with parameter μ_{SU}^i . The arrival rate of SUs depends on the global state ($\vec{n} \in F$) of the system. The arrival rate of SUs in WSP i is given by

$$\lambda_{SU}^i(\vec{n}) = \lambda_{new,SU}^i + \sum_{j \neq i} \lambda_{SU}^{j,i} + \lambda_{out,SU}^i, \quad \text{if } n(i) < K_i. \quad (2.7)$$

As indicated in the first scheme, the matrix \mathbf{Q} of transitions is obtained over the feasible state space F . Then, we derive a new system of equations like (2.2), and find the global steady state denoted by $\bar{\pi}$ ($\bar{\pi} = \{\bar{\pi}(\vec{n}), \vec{n} \in F\}$). We solve the problem in two ways, by constructing the above matrix \mathbf{Q} and by the approximative method, to derive the steady state probabilities.

To obtain the matrix \mathbf{Q} , let us define a new class c by SU^- , that represents the foreign SUs. In addition to the transitions defined in (2.1), we have

$$\begin{aligned} q_{\{\vec{n}, \vec{n}_{i-}^{SU-}\}} &= n_{SU}^{-i} \cdot \mu_{SU}^i, \\ q_{\{\vec{n}, \vec{n}_{i+}^{SU-}\}} &= \lambda_{SU}^{-i} \cdot \mathbf{1}_{\{n_{PU}^{-i} \neq 0\}}, \\ q_{\{\vec{n}, \vec{n}_{i+j-}^{PU, SU-}\}} &= \lambda_{PU}^i, \\ q_{\{\vec{n}, \vec{n}_{i+j-}^{SU, SU-}\}} &= \lambda_{SU}^i. \end{aligned} \quad (2.8)$$

For the approximative solution we define the sub state space for WSP i as follows

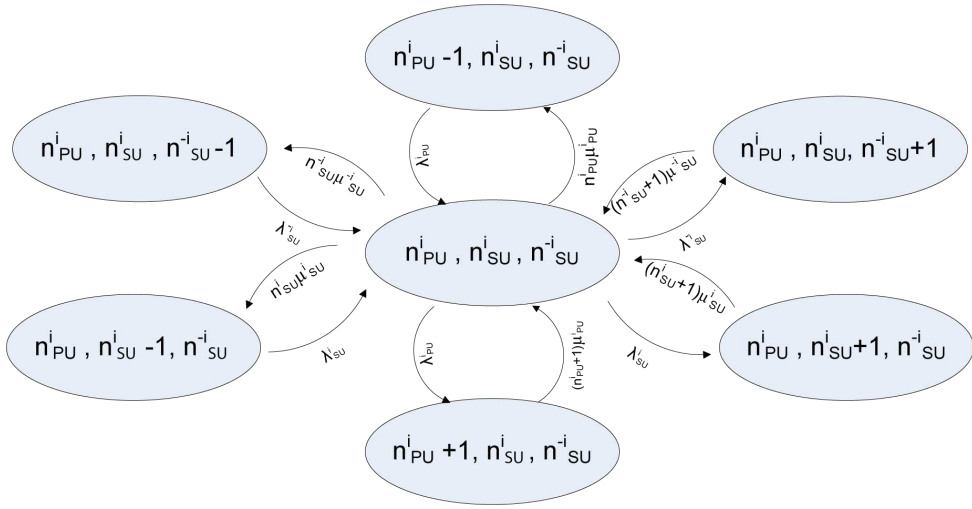
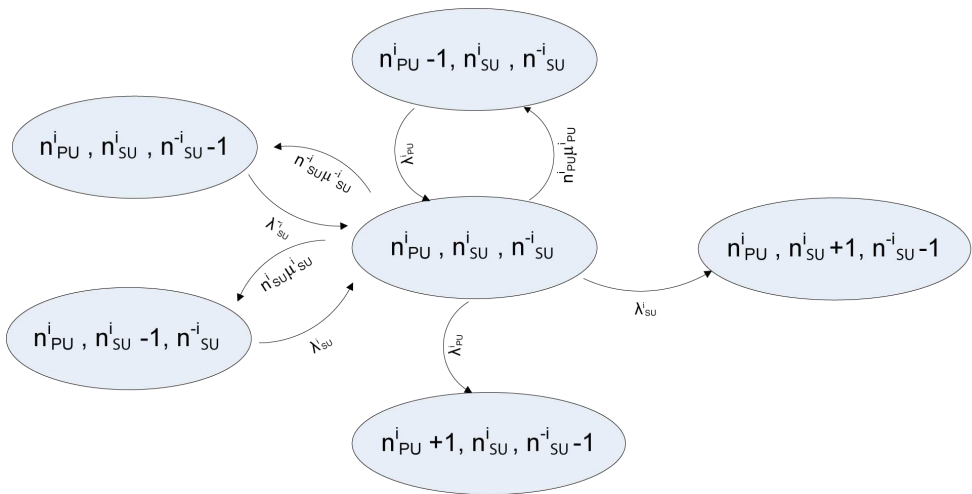
$$F_i = \{\vec{n}_i \in \mathbf{N}^3 \mid n(i) \leq K_i; i = 1, \dots, N\},$$

where $\vec{n}_i = (n_{PU}^i, n_{SU}^i, n_{SU}^{-i})$. The steady state probability of WSP i is defined by

$$\bar{\pi}_i = \{\bar{\pi}_i(\vec{n}_i) \mid \vec{n}_i \in F_i\},$$

This steady state probability is given by solving the set of balance equations [30]. We distinguish four cases:

1. The states satisfying $n(i) < K_i$, $n_{PU}^i < Th_i$ and $n_{SU}^{-i} \neq 0$ and it represents the non saturated states.
2. If we have states satisfying $n(i) = K_i$ and $n_{PU}^i < Th_i$, the arrival of a new PU gives rise to an interrupted SU. If a foreign SU occupies a channel, he is dropped first, if it's not the case, an own SU is dropped.
3. If the states satisfy the conditions $n(i) = K_i$ and $n_{SU}^{-i} \neq 0$, the arrival of a new own SU gives rise to an interrupted external SU.
4. If the states satisfy the conditions $n(i) = K_i$, $n_{PU}^i < Th_i$ and $n_{SU}^{-i} = 0$, the arrival of a new PU gives rise to an interrupted own SU.

FIGURE 2.6: System state transit for $n(i) < K_i$, $n_{PU}^i < Th_i$ and $n_{SU}^{-i} \neq 0$ FIGURE 2.7: System state transit for $n(i) = K_i$, $n_{PU}^i < Th_i$ and $n_{SU}^{-i} \neq 0$

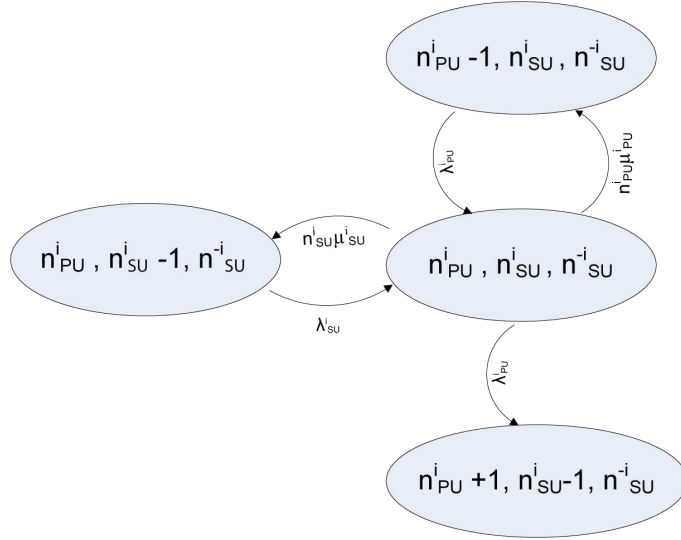


FIGURE 2.8: System state transit for $n(i) = K_i$, $n_{PU}^i < Th_i$ and $n_{CR}^{-i} = 0$

Figures (2.6,2.7,2.8) show the transit rate diagram in the priority scheme. The summation of all steady state probabilities satisfies the normalization constraint $\sum_{\vec{n}_i \in F_i} \bar{\pi}_i(\vec{n}_i) = 1$. We solve the set of the linear equations and consequently the steady state probability distribution by using the *SOR* [30] method as in the first scheme.

2.4.2 Calculation of migration rates

A SU from WSP j decides to handoff to another WSP if $n(j) = K_j$ and $n_{SU}^{-j} = 0$ (i.e., WSP j uses all its own resources without the presence of foreign SUs). Then, the arrival rate (migration) of SUs from WSP j to i is given by

$$\lambda_{SU}^{j,i} = \sum_{\vec{n} / n(j)=K_j, n(i) < K_i, n_{SU}^{-j}=0} \frac{\bar{\pi}(\vec{n})}{a(\vec{n})} \lambda_{new,SU}^j, \quad (2.9)$$

where

$$\bar{\pi}(\vec{n}) = \frac{1}{\beta} \prod_{i=1}^N \bar{\pi}_i(\vec{n}_i), \quad (2.10)$$

and $\beta = \sum_{\vec{n} \in F} \prod_{i=1}^N \bar{\pi}_i(\vec{n}_i)$. In order to obtain the arrival rate $\lambda_{SU}^i(\vec{n})$ from (2.7), we need first to compute $(\lambda_{SU}^{j,i}, j \neq i)$. To do this we apply again the Migration rate computing algorithm defined previously by replacing the equations (2.3), (2.4) and (2.5) by these analogous (2.7), (2.10) and (2.9) respectively. Note that the arrival rate $\lambda_{out,SU}^i$ has the same value as in the previous scheme.

2.5 Performance evaluation

We have used three classic QoS metrics to evaluate the performance of the system: blocking probability, dropping probability and spectrum utilization metric. Each is calculated based on the state and transition probabilities for the two schemes as follows:

2.5.1 Blocking probabilities

Let $P_B(i, PU)$ be the blocking probability for PUs calls belonging to WSP i . A PU is blocked if he arrives while its home WSP is already using all its available resources dedicated to PUs (i.e., $n_{PU}^i + 1 > Th_i$). Therefore, the probability of blocking for the two schemes is expressed as follows:

$$P_B(i, PU) = \sum_{\vec{n} \in E} \pi(\vec{n}) \cdot \mathbf{1}_{\{n_{PU}^i + 1 > Th_i\}}.$$

Similarly, $P_B^1(SU)$ (resp. $P_B^2(i, SU)$) are the SUs blocking probabilities for the No priority scheme (resp. for the priority scheme). However, the conditions for blocking are different depending on the scheme. Indeed, in order to be blocked many conditions must be satisfied when a SU arrives:

- A new SU in the no priority scheme is blocked if all resources in all WSPs are occupied ($\sum_{k=1}^N n(k) = M$). Therefore, the blocking probability is

$$P_B^1(SU) = \sum_{\vec{n} \in E} \pi(\vec{n}) \cdot \mathbf{1}_{\{\sum_{k=1}^N n(k) = M\}}. \quad (2.11)$$

- A new SU using the priority scheme is blocked if all resources in all WSPs are occupied and the own WSP of this SU is fully occupied by its own users ($n_{SU}^{-i} = 0$). Then the blocking probability is

$$P_B^2(i, SU) = \sum_{\vec{n} \in F} \bar{\pi}(\vec{n}) \cdot \mathbf{1}_{\{\sum_{K=1}^N n(k) = M, n_{SU}^{-i} = 0\}}. \quad (2.12)$$

2.5.2 Dropping probabilities

Once service begins, the primary connections are never interrupted or dropped for the two schemes (i.e. $P_D^1(i, PU) = P_D^2(i, PU) = 0$). Therefore, only SUs (own and foreigner) can be dropped. Concerning the priority scheme, a SU using a channel in WSP i is

dropped only if a new PU arrives and the condition $n_{PU}^i < Th_i$ occurs. Then the dropping probability is given by

$$P_D^1(i, SU) = \sum_{\vec{n} \in E} \pi(\vec{n}) \cdot \mathbf{1}_{\{n(i)=K_i\}} \cdot \mathbf{1}_{\{n_{PU}^i < Th_i\}}.$$

As for the priority scheme a SU in his own WSP i is dropped if a new PU arrives and the two conditions $n_{PU}^i < Th_i$ and $n_{SU}^{-i} = 0$ occur. Then the dropping probability is given by

$$P_D^2(i, SU) = \sum_{\vec{n} \in F} \bar{\pi}(\vec{n}) \cdot \mathbf{1}_{\{n(i)=K_i\}} \cdot \mathbf{1}_{\{n_{PU}^i < Th_i\}} \cdot \mathbf{1}_{\{n_{SU}^{-i}=0\}}.$$

Several conditions must occur in order to drop a foreigner SU when a new arrival event to WSP i happens. These conditions differ slightly, depending on whether the incoming user is a primary or a secondary. In both cases, these two conditions must occur:

- All the M channels in the system are occupied $\sum_{k=1}^N n(k) = M$. (*i*)
- WSP j is using all resources that it physically possesses by its own users (i.e. no external SUs). Formally we have $n(j) = K_j$ and $n_{SU}^{-j} = 0$. (*ii*)

If the user that arrives is primary, the following condition (*iii*) must also be true :

- WSP i uses less resources than its specified threshold ($n_{PU}^i < Th_i$). (*iii*)

Whereas if the user that arrives is cognitive, condition (*iv*) must occur :

- WSP i uses less resources than its physical capacity ($n_{SU}^{-i} \neq 0$). (*iv*)

Summing up all the results implies that the dropping probability in a WSP i of a SU making a handover from WSP j by another SU from $i, i \neq j$ is given by

$$P_D^2(j, i, SU) = \left(\sum_{\vec{n} \in F} \bar{\pi}(\vec{n}) \mathbf{1}_{\{n_{PU}^i < Th_i\}} + \sum_{\vec{n} \in F} \bar{\pi}(\vec{n}) \mathbf{1}_{\{n_{SU}^{-i} \neq 0\}} \right) \cdot \mathbf{1}_{\{\sum_{k=1}^N n(k) = M, n_{SU}^{-j} = 0\}}.$$

2.5.3 Spectrum utilization

We define the total spectrum or bandwidth utilization as follows

$$U = \frac{1}{M} \sum_{\vec{n} \in S} P(\vec{n}) \sum_{i=1}^N n(i),$$

TABLE 2.2: Set of parameters used in simulations

Parameters	Network 1	Network 2	Network 3
K	12	10	7
Th	7	5	3
μ_{PU}	0.3	0.4	0.4
μ_{CR}	0.3	0.4	0.4
$\lambda_{new,CR}$	Variable	0.4	0.3
$\lambda_{out,CR}$	0.3	0.3	0.3

where \mathcal{S} represents the space of states (E or F) and $\mathbf{P}(\vec{n})$ the steady state probability ($\pi(\vec{n})$ or $\bar{\pi}(\vec{n})$) depending on the scheme.

2.6 Numerical results

We turn in this section to study a concrete example that will allow us to measure different metric performances of the system, and the various parameters that influence on that performances. Illustrative numerical examples are presented to demonstrate the interaction between the performance metrics and critical settings and to have a comparison with the theoretical analysis. We consider a system consisting of three WSPs ($N = 3$). The set of parameters used in this section is summarized in table 2.2.

2.6.1 Comparison and impact of our schemes

In what follows we denote by **Sch1** the no priority scheme and by **Sch2** the priority one, and also we will refer in figures to our approximative method by (**A**) and the exact method by (**E**). In all figures, the arrival rate is in (call/sec). We will start by studying the case of two WSPs ($N = 2$). λ_{PU}^1 and λ_{PU}^2 were obtained from figure 2 that was used to develop a baseline to which SU improvements could be compared. Each service provider must deliver a certain level of QoS to its primary users based on the blocking probability $P_B(i, PU)$. It is then important to know the maximum PUs arrival rate that can be supported by the system while achieving this QoS. We plot in figure 2 the blocking probability of primary users for the two schemes to show the maximum arrival rate supported while limiting blocking at 1%. The result obtained is quite normal, since the blocking probability of PUs depends only on the PUs arrival rate. We note that under this setting, the maximal arrival rate for PUs is $\lambda_{PU}^1 = 1.2$ for the first WSP and $\lambda_{PU}^2 = 0.5$ for the second. We'll use these values in the rest of numerical examples.

The difference between exact and approximative method, is that we consider an independence between all WSPs in the system. Indeed, we considered this hypothesis based on

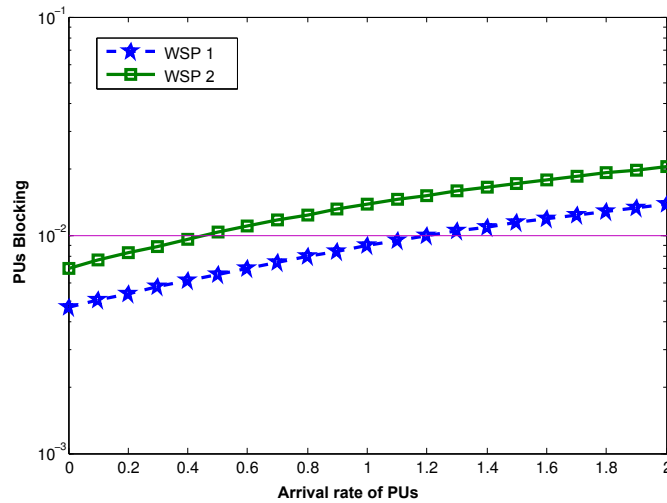


FIGURE 2.9: Blocking probabilities of primary flows as a function of PUs arrival rate.

the fact that each WSP is independent. This would mean that these service providers do not exchange their settings, nor reveal their resources for others. The difference between stationary distribution calculated from both approximative and exact method is about 2.10^{-4} in most cases, which is small enough to confirm that our main hypothesis reduces the calculating time considerably and helps to benefit from the reasons discussed above without changing the characteristics and the nature of the system. This small variation between the two methods appears clearly in all figures (figure 2.10, 2.11, 2.12 and 2.13).

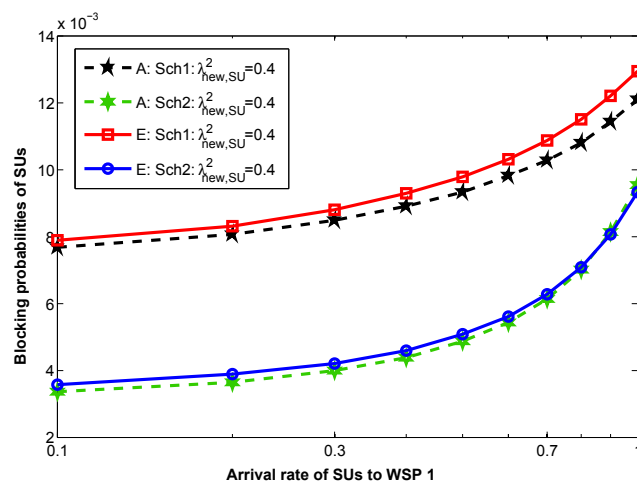


FIGURE 2.10: Blocking probabilities of CR flows-Varying the network 1 cognitive arrival rate for approximative and exact method.

In figure 2.10 we depict cognitive blocking probability as a function of arrival rate of

SUs to the first WSP. When a new SU asks to have service in its home WSP, it has more chance with **Sch2** to find either an empty channel or to drop an external SU. Unlike **Sch1**, where a new own SU looks only for an empty channel. Indeed, by applying priority scheme, we can have a lower blocking probability than that obtained with the first scheme by nearly 35%, which is an interesting improvement for performance of SUs.

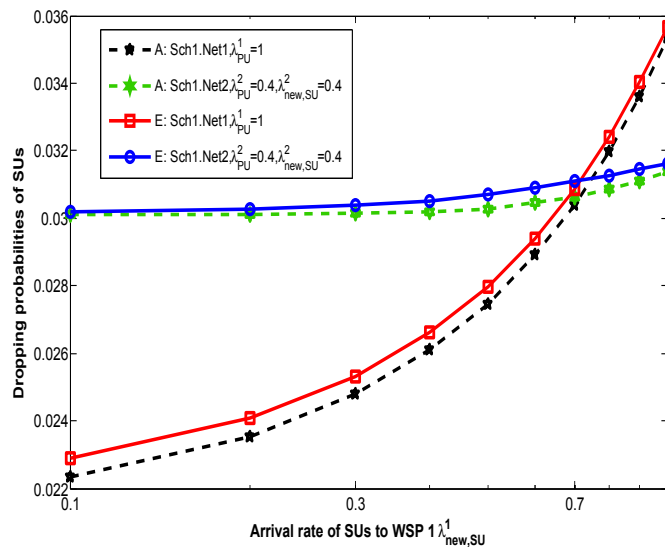


FIGURE 2.11: Dropping probabilities of CR flows using Sch1

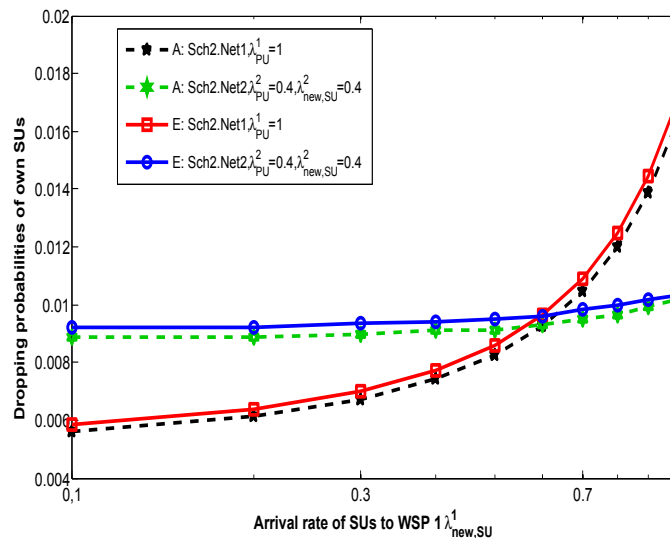


FIGURE 2.12: (b) Dropping probabilities of own CR flows using Sch2

According to figures 2.11, 2.12 and 2.13 dropping probability was improved (i.e. decreased) from scheme 1 to scheme 2. Also in scheme 2 the priority has a direct impact on the values of dropping. Indeed, for small and medium values of arrival rate ($\lambda_{new,CR}^1$) we notice that the dropping in the first WSP (figure 2.11 and figure 2.12) is lower than

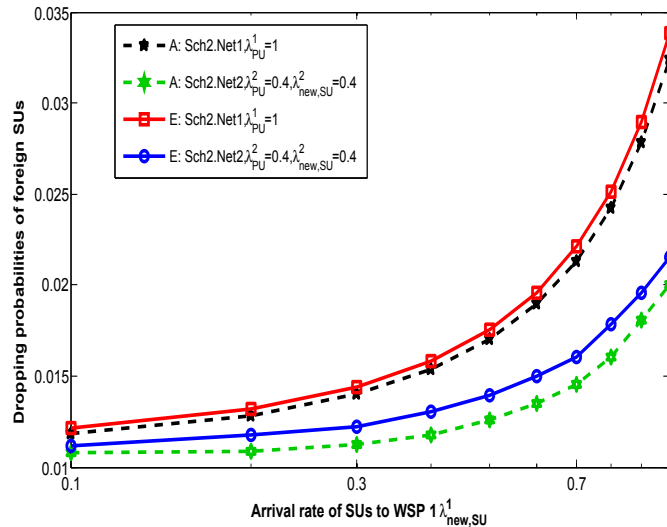
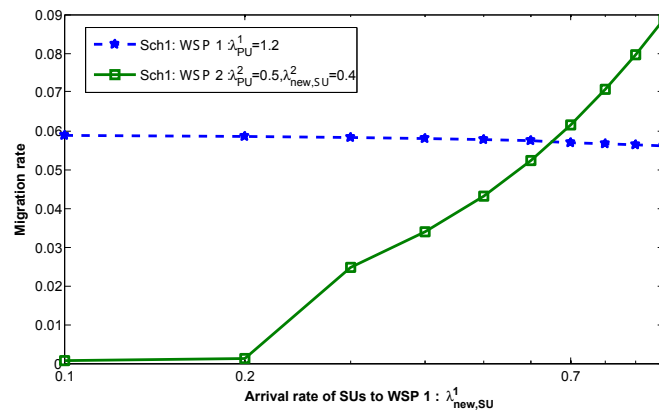


FIGURE 2.13: Dropping probabilities of foreign CR flows using Sch2

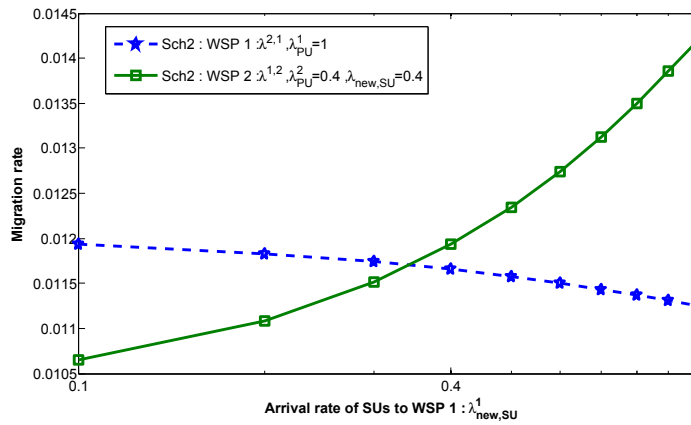
dropping in the second one. However this behavior is not present in (figure 2.13). This is resulting from the politic followed in each scheme. Indeed, in the first scheme the



(a)

FIGURE 2.14: Migration rate to each network for Sch1-Varying the network 1 cognitive arrival rate.

migration rate to the second WSP is high (figure 2.14), and this is resulting from the growth of the number of SUs that arrives to the first WSP and consequently the occupation of all channels K_1 . The saturation of WSP 1 generates more handover and more SUs in the second WSP and as a result more dropping. As for the second scheme, priority between SUs decreases considerably the values of migration rates (figure 2.15) (i.e an incoming SU has a high probability to be served in his own WSP), but foreign SUs are more dropped in the first WSP because they are dropped by both primary ($\lambda_{PU}^1 = 1.2$) and own SUs.



(b)

FIGURE 2.15: Migration rate to each network for Sch2-Varying the network 1 cognitive arrival rate.

However, own SUs are dropped more in the second WSP and it is related to the arrival rate of this kind of users ($\lambda_{new,SU}^2 = 0.4$ and $\lambda_{new,SU}^1 < 0.6$) and also the number of channels available in each WSP. But we can remark that once $\lambda_{new,SU}^1$ exceeds the value of 0.6 (which represents the saturation value for $K_1 = 12$ channels), curves change and depend more on the arrival rate of PUs ($\lambda_{PU}^1 = 1.2, \lambda_{PU}^2 = 0.5$). Priority scheme show through values (0.017 as maximum value for own and 0.034 for foreign SUs in the first WSP, 0.01 as maximum value for own and 0.021 for foreign in the second WSP, nearly 50%) that users who use a part of their traffic in a cognitive manner (when their demand are not delay-sensitive) have less risk to be dropped before they finish their service comparing to external users.

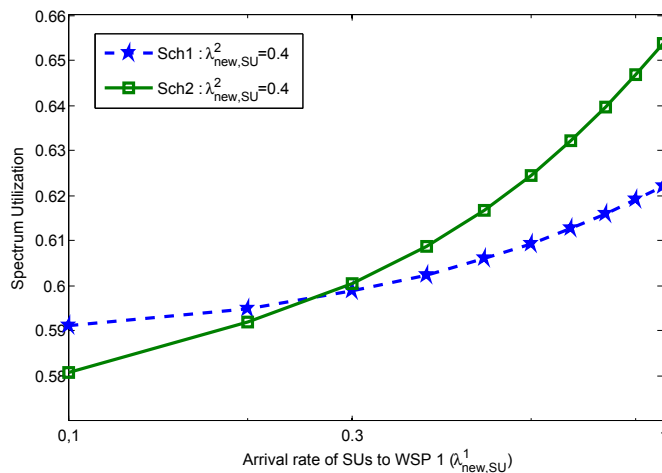


FIGURE 2.16: Spectrum utilization-Varying the network 1 cognitive arrival rate in call/sec.

Improving spectrum utilization is an important task for enhancing and sustaining the growth of mobile users with limited spectrum. We plot in figure 2.16 the spectrum utilization for both schemes. For low traffic (small values of cognitive arrival rate), applying priority between own and foreign SUs can antagonize and penalize spectrum utilization. That's why, it's better for a service provider to apply the **Sch1** in this situation. But, when arrival rate of SUs starts to grow (medium and high traffic) priority scheme works better and improves more the spectrum utilization. This result is coming from the behavior of the three kind of users. own SUs are less blocked and dropped in the **Sch2**, which results more spectrum utilization and more time using the system.

2.6.2 Using approximative solution with $N=3$

In this sub section we examine the case where the number of networks is greater than 2 WSPs ($N > 2$). We recall that the exact solution takes more time and becomes more complex when N increases. For this reason, we use our approximative solution in the next simulations with $N = 3$. In figure 2.17 we plot the blocking probability of SUs for the two schemes. The results show that even with multiple WSPs, the priority scheme still offer less blocking for own SUs for the same reasons discussed before.

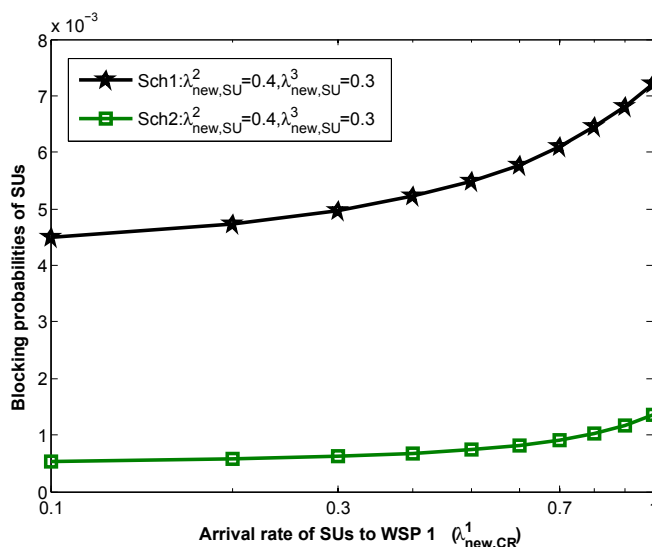


FIGURE 2.17: Blocking probabilities of CR flows-Varying network 1 cognitive arrival rate (call/sec) for approximative solution with 3 sub-networks.

We can make the same remark for the case of CR dropping probability illustrated in figures 2.18, 2.19 and 2.20. For small values of $\lambda^1_{new,SU}$ the dropping in WSP 2 and 3 is constant, and starts growing with the increasing of the arrival rate of SUs. Indeed, the

migration from WSP 1 to the others starts after saturation. Also, foreign SUs are less dropped in small WSPs (figure 2.20) because the migration rate to these WSPs is low.

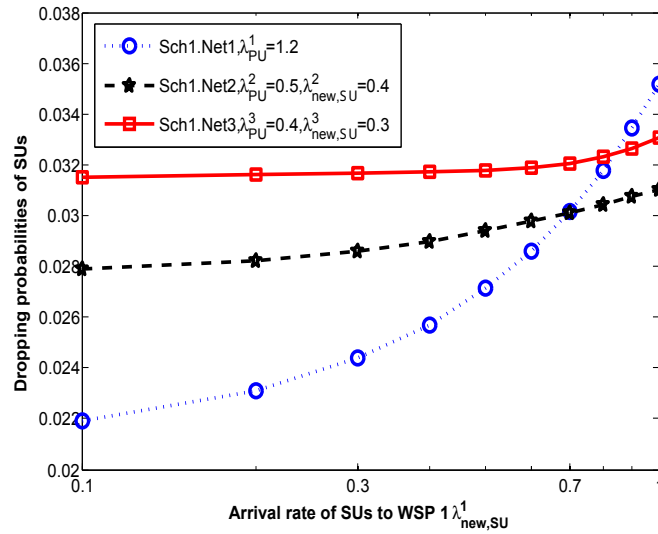


FIGURE 2.18: Dropping probabilities of CR flows

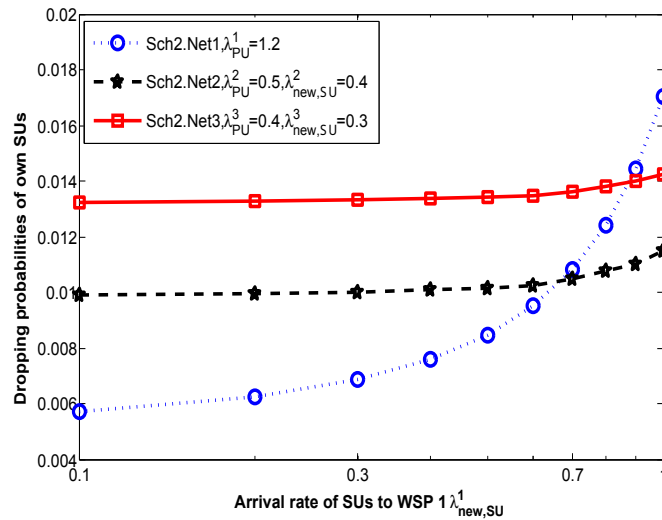


FIGURE 2.19: Dropping probabilities of own CR flows

2.7 Conclusion

In this chapter, we have studied the QoS and the performance evaluation in wireless networks. The system proposed here is a set of wireless service providers. We define three different kinds of users: primary users with dedicated channels, mixed users that

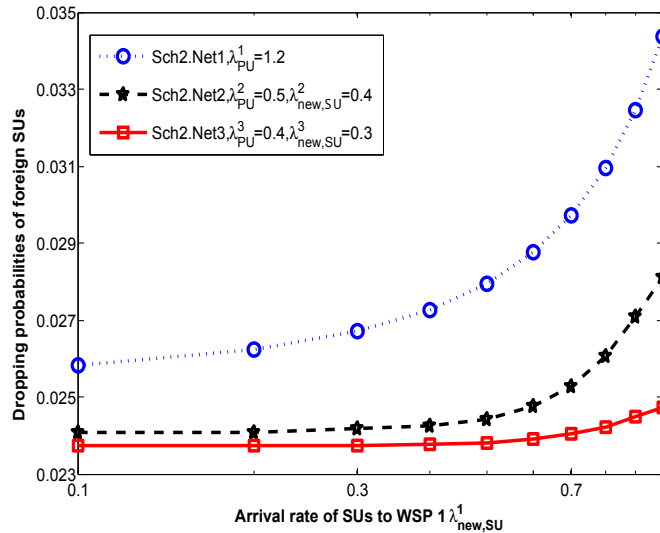


FIGURE 2.20: Dropping probabilities of foreign CR flows

have the possibility to split their traffic into real time and best effort traffic and finally SUs who sense the channels for spectrum holes.

Moreover, a dynamic access control for SUs was proposed for two schemes. Indeed, we propose a scheme where the access control is related to the total number of SUs present in the system (no priority between them), and to the threshold fixed by the WSP. While in the second scheme, more priority is given to what we called "own SUs". In fact, own SUs could be dropped in their home WSP only by PUs. Whereas foreign SUs could be dropped by both PUs and own SUs of each WSP. Furthermore, we have seen that improving the service time of SUs is possible with respect to the QoS offered to PUs.

The model developed describes the interaction between users in one side, and between users and service providers in the other side. The system is modeled by a Markov process, with continuous time and finite state space. Using this Markov process, we have calculated the exact solution and proposed an approximation to make the problem much easier to solve, without changing its characteristics. Moreover, the application of this approximation is more realistic in this context, since a service provider has only partial information about the system. We show numerically that the two solutions are too close from each other with a negligible difference.

In addition, several numerical results are presented in this chapter in order to analyze the two schemes of our study. Through these experiments, it has been verified that priority levels applied to SUs allows an improvement in QoS or the support of additional best effort users without deteriorating the QoS of PUs. We believe that how a service provider should choose the threshold is a crucial task. Indeed, decreasing the threshold

could produce a high migration rate of SUs to other WSPs and brings down their performance. The problem becomes one of noncooperative games and could be the extension of this chapter in a future work.

Chapter 3

Optimal resource allocation in wireless virtual networks: Complete and Partial Information

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3.1 Introduction

The deployments of wireless Local Area Networks (WLANs) are experiencing huge growth due to inexpensive and availability of network equipments as the integrated WLAN cards in almost all laptops and smartphones. As the number of users using wireless technologies becomes larger, the demand for the network bandwidth usage has increased. In contrast to wire-line network architectures which can often provide a guaranteed quality of service to users by strict division of the network resources, the shared nature of the wireless domain inherently implies that the performance of each mobile depends on the resources allocated to others. Indeed, the bandwidth capacity who is typically considered as a scarce resource is limited. In order to provide a certain level of Quality of Service (QoS) for different applications to users, providers require some efficient bandwidth management techniques.

Recently, bandwidth management schemes were the subject of several studies to improve the quality of service. For instance, the authors of [31] propose an algorithm to determine the associations between the user and the access point to achieve a fair bandwidth allocation. Different bandwidth management techniques for WLANs that use a hybrid load balancing scheme are presented and compared in [32]. It is clear that bandwidth management techniques could improve the QoS, but it can also impair the performances. Indeed, according to [33], Medium bandwidth consumption increases due to the control messages sent by access points, and messages retransmission after collisions. As a result, Access point throughput decreases as the number of users increase.

Apart from bandwidth management, the power of transmission is an important parameter for a growing class of users who want to transmit signal cheaper and conserve energy. For users utilizing battery-powered communication equipment, it is advantageous or even necessary to minimize energy consumption while conserving the same QoS. In [34] and [35], authors investigate the energy consumption of wireless network interfaces and different network protocols in detail. They also classify power management policies into different categories. Another aspect is studied in [36] and [37]. The authors are interested in power control as a mean of balancing received power levels or guaranteeing a certain signal-to-interference ratios (SIRs).

From the provider's point of view, there has been much research and interest in maximizing the revenue and capacity expansion. It is well known that minimizing interference using power control increases capacity [5],[6],[7],[8] and also extends battery life. Recently, an alternative approach to the power control problem in wireless systems based on an economic model has been offered [38],[39],[40],[41],[42]. In this model, a utility function representing service preferences for each user quantifies the level of satisfaction he gets from using the system resources.

Other works study the impact of access prices on the congestion management practices and revenue of a service provider, operating on a single link with fixed capacity. Consumer data rate allocation can be determined by optimal prices in a competitive market on one hand, or the revenue maximizing prices in a monopoly provider market on the other hand. This chapter explores the latter point and represents the most favorable outcome to the provider and possibly the least favorable outcome to the consumers. Access pricing is typically in the form of a flat rate [43],[44], also referred to as a linear rate, a pricing structure that charges a single fixed fee for a service, regardless of usage. For Internet service providers, flat rate is access to the Internet at all hours and days of the year (linear rate) and for all customers of the service provider at a fixed and cheap cost. Flat rate is common in broadband access to the Internet in many countries.

User demand for data changes over hours of the day and days of the week, resulting in peak usage of networks that can be significantly high compared to average usage. Providers face a mismatch between their revenue from average usage and cost incurred from peak usage of networks. An intuitive solution for providers to this problem is to increase the price in periods of peak usage of bandwidth. This solution is not effective. Indeed, in [45] considerations on billing management and price simplicity discourage frequent changes in prices over time. This limitation to manage peak aggregate demand through price variations can result in potential loss of revenue. An overview of the various models of pricing have been proposed, and can be found in [46].

In this chapter, we consider the revenue maximization problem from the viewpoint of a mobile virtual network operator (MVNO). An MVNO is a wireless communications service provider that does not own its own spectrum and usually does not have its own network infrastructure. Instead, MVNO's have business arrangements with traditional mobile operators to buy minutes of use for sale to their own customers. We quantify that the revenue of the MVNO is from a flat price proposed to consumers or users. Flat pricing is generally considered as the preferred choice of users [45]. Users decide to accept the service from providers, if their net utility is positive or at least not negative. The provider can either increase his revenue by adjusting the price of service, or by determining the optimal number of users and the optimal amount of bandwidth to lease. Despite a large number of works on pricing schemes, revenue-maximizing via computation of the optimal number of users is relatively unexplored. Our objective is to provide a scheme that would achieve (or approximately achieve) the optimal solution for the provider, taking into account the strategy of users, the interference influence and bandwidth management. We start by finding a near-optimal solution in a static environment, where the channel gain of users (system state) doesn't change over time. In this case the provider has a complete information of the system. Then we extend the model to a more realistic and general case, where the provider has information concerning users that accept the service at a given instant. In other words, the users that have a negative utility and consequently refuse the service, their channel state is hidden from the provider. The model becomes a dynamic system where channel state of users changes with time. We are faced to a partially observable Markov decision processes (POMDP).

The rest of the chapter is organized as follows. Section 3.2 presents the setup for the revenue maximization problem. We start by a model without interferences, based on which we include interference between users. In Section 3.3, based on a POMDP framework, we introduce the case of partial information. Section 3.4 presents some numerical examples, and finally, section 3.5 summarizes our observation and conclude the chapter.

3.2 Revenue maximization in a static environment

3.2.1 Model without interference

We consider an MVNO that can serve a maximum of N users that pay a fixed cost. We assume that there is no interference between users since provider supplies different bandwidth frequencies to different users and shares the leased bandwidth frequency equally between the users. Then user's i payoff is given as follows:

$$u_i = \frac{W}{n} \ln \left(1 + \frac{h_i P_i}{(W/n)\sigma^2} \right) - C_F,$$

where C_F is the flat fee for access to the network service, P_i is the transmission power of user i , h_i is the fading channel gain, σ^2 is the background noise, W is the leased bandwidth frequency and n is the number of users ($n \leq N$) that accept the service as described bellow.

We assume that user i accepts the service if his payoff u_i is non-negative and he rejects the service otherwise. Indeed, if the user pays more than he gets, he has no interest to use the service. Without loss of generality we can assume that powers received by users are ranked in decreasing order by induced applied power, i.e.

$$h_1 P_1 \geq h_2 P_2 \geq \dots \geq h_n P_n.$$

Then since u_i is increasing by $h_i P_i$, the provider intends to serve all users accepting the service, which means, the n users that their payoff satisfies the condition $u_n \geq 0$. Thus,

$$\frac{W}{n} \ln \left(1 + \frac{h_n P_n}{(W/n)\sigma^2} \right) \geq C_F. \quad (3.1)$$

The payoff of the provider is defined as the total fee it charges the users minus expenses for leasing the frequency bandwidth, which we assume is proportional to the frequency bandwidth, i.e.

$$v_P(W, n) = nC_F - C_W W, \quad (3.2)$$

where C_W is the cost for frequency bandwidth unit and it is assigned by authority. The payoff to the authority is

$$v_A(C_W) = C_W W.$$

Since the provider has to lease bandwidth from authority with a cost C_W per unit of bandwidth, the best choice is to lease only and exactly the amount of bandwidth that would be used by users. Indeed, there is no need for the provider to lease an extra amount of bandwidth knowing that it will not be used. It is a waste in terms of revenue.

Then the provider can increase his revenue by leasing the optimal amount of bandwidth satisfying the following condition.

Theorem 3.2.2. Let W^* be the optimal bandwidth leased by the provider. The last user (n) accepted by the provider satisfies the following condition

$$\frac{W^*}{n(W^*)} \ln \left(1 + \frac{h_n P_n}{(W^*/n(W^*))\sigma^2} \right) = C_F. \quad (3.3)$$

Proof: Suppose that

$$\frac{W^*}{n(W^*)} \ln \left(1 + \frac{h_n P_n}{(W^*/n(W^*))\sigma^2} \right) > C_F.$$

then there exist an ξ of bandwidth such that : $\bar{W} = W^* - \xi$ which implies that

$$\begin{aligned} C_F &< \frac{\bar{W}}{n(W^*)} \ln \left(1 + \frac{h_n P_n}{(\bar{W}/n(W^*))\sigma^2} \right) \\ &< \frac{W^*}{n(W^*)} \ln \left(1 + \frac{h_n P_n}{(W^*/n(W^*))\sigma^2} \right). \end{aligned}$$

The number of users that can be served by \bar{W} is greater than the number of users that can be served by W^* . Then we have $n(\bar{W}) \geq n(W^*)$ which gives $u_i(W^*) > u_i(\bar{W})$. Also, the profit of the provider using \bar{W} is

$$v_P(\bar{W}, n(\bar{W})) = n(\bar{W})C_F - C_W \bar{W}$$

knowing that $\bar{W} > W^*$, then $v_P(\bar{W}, n(\bar{W})) > v_P(W^*, n(W^*))$. Which is a contradiction since we have considered that W^* is the optimal bandwidth that gives the maximum profit. Then the result follows. ■

The strategy of the provider can not be accepting the maximal number of users by leasing the corresponding bandwidth for them to maximize his revenue. Indeed, it is clear that the number of users will increase if the provider offers more bandwidth. But due to the decreasing induced applied power $h_i P_i$, at a certain value of W and n , the condition that insure the QoS to users will not be satisfied any more. Since the number of users n is discrete and without loss of generality, we suppose that bandwidth takes values from a discrete set $\{W_1, W_2, \dots, W_n\}$, with W_i means the amount of bandwidth required to accept i users.

Resolving the problem theoretically is not easy in standard SINR regime. We have to characterize the number of users accepting the service. However, based on the user's payoff we can not express n as a function of the bandwidth W . In this chapter, we will approach the optimal solution by considering the case of high SINR regime and show by

simulations that this is a near-optimal solution to the revenue maximization problem. According to theorem 3.2.2, if we consider the optimal bandwidth, equation (3.3) under high SINR regime becomes:

$$\frac{W^*}{n(W^*)} \ln \left(\frac{h_n P_n}{(W^*/n(W^*))\sigma^2} \right) = C_F. \quad (3.4)$$

Then we have :

$$n = -\frac{W^*}{C_F} \text{LambertW} \left(\frac{-C_F \sigma^2}{h_n P_n} \right). \quad (3.5)$$

The payoff of the provider can be rewriting as :

$$v_P(W^*) = -W^* \text{LambertW} \left(\frac{-C_F \sigma^2}{h_n P_n} \right) - C_{W^*} W^*. \quad (3.6)$$

It is easy to verify that $v_P(W^*)$ is a concave function with a global maximum at

$$h_n P_n = \frac{C_F e^{C_{W^*} \sigma^2}}{C_{W^*}} \quad (3.7)$$

Then there exists an optimal number of users that maximizes the profit of the provider. This optimal number of users is given in the following theorem

Theorem 3.2.3. If n^* is the optimal number of users that the provider has to accept to maximize his profit, then

$$n^* = \text{argmin} \left\{ n/W_{n+1} - W_n > \frac{C_F}{C_W} \right\} \quad (3.8)$$

This result follows from the concavity of v_P . We have to look for the threshold of the number of users that if we exceed it, the payoff decreases. Then if

$$v_P(n) > v_P(n+1)$$

$$nC_F - C_W W(n) > (n+1)C_F - C_W W(n+1)$$

which gives

$$W(n+1) - W(n) > \frac{C_F}{C_W}$$

3.2.4 Model with interference

In this subsection we take into account interferences in the model. Hence, the utility of users will decrease when interference becomes high, which will impact the revenue of

the provider. In this case, the payoff of user i will be given as follows:

$$u_i = \frac{W}{n} \ln \left(1 + \frac{h_i P_i}{(W/n)\sigma^2 + I} \right) - C_F, \quad (3.9)$$

where $I = \sum_{m \neq n} h_m P_m$ is the interference noise.

Let us derive the expression of the optimal bandwidth W^* . The optimal bandwidth to lease is the solution of the following equation

$$\ln \left(1 + \frac{h_n P_n n}{W\sigma^2 + I} \right) - \frac{h_n P_n n \sigma^2 W}{(W\sigma^2 + I)(W\sigma^2 + I + h_n P_n n)} - C_W = 0. \quad (3.10)$$

In high SINR regime the optimal frequency bandwidth is simplified, and is the solution of the equation

$$\ln \left(\frac{h_n P_n n}{W\sigma^2 + I} \right) - \frac{W\sigma^2}{W\sigma^2 + I} - C_W = 0. \quad (3.11)$$

in the closed form W^* becomes

$$W^* = \frac{1 - \text{LambertW} \left(\frac{I e^{1+C_W}}{h_n P_n n} \right)}{\text{LambertW} \left(\frac{I e^{1+C_W}}{h_n P_n n} \right)} \frac{I}{\sigma^2} \quad (3.12)$$

The number of users accepted by the provider in presence of interference is

$$n = -\frac{W^*}{C_F} \text{LambertW} \left(\frac{-C_F(W^*\sigma^2 + I)}{h_n P_n W^*} \right). \quad (3.13)$$

Finally, the profit of the provider considering interferences between users has the following form

$$v_P(W^*) = -W^* \text{LambertW} \left(\frac{-C_F(W^*\sigma^2 + I)}{h_n P_n W^*} \right) - C_{W^*} W^*. \quad (3.14)$$

As in the case without interference, we can verify that the profit of the provider is a concave function with a global maximum corresponding to the optimal number of users the provider has to accept. Theorem 3.2.3 still applicable in this case.

3.3 Revenue maximization in a dynamic environment

Unlike the static model, we propose in this section a dynamic framework where channel state of users changes over time. Indeed, the provider can not know the state of users that refuse the service at a time slot t . Which means that based on observations,

the provider knows only the state of users that accept the service at a time t . He observes partially the state of the system. The described problem is inherently a Partially Observable Markov Decision Processes (POMDP) [47] problem. A POMDP is used to model a decision process that include uncertainty in action effects [48]. In this section, we develop a decision-theoretic approach in a wireless network. We show that the model specified in the previous section can be modeled by a POMDP. The optimal number of users and the optimal bandwidth W corresponds to a policy for this POMDP. Let us define the state of a user $i \in \{1, \dots, N\}$ at time slot t by the channel quality h_i noted by $S_i(t) = \{h_i\}$. The global state of the system at time t is denoted by the vector $S(t) = \{S_1(t), S_2(t), \dots, S_N(t)\}$. For sake of simplicity, we consider that each user can either have a good or a bad channel quality denoted respectively by h_H and h_L . The transition probabilities for user i are denoted by $P(s'|s) = P(S_i(t) = s' | S_i(t-1) = s)$. Let α (resp., β) be the probability that a high quality channel (resp., a low quality) is followed by a high quality. Formally, $\alpha = P(S_i(t) = h_H | S_i(t-1) = h_H)$ and $\beta = P(S_i(t) = h_H | S_i(t-1) = h_L)$. Let P be the channel quality transition matrix,

$$P = \begin{pmatrix} 1 - \beta & \beta \\ 1 - \alpha & \alpha \end{pmatrix}$$

We assume that the transition probabilities are known by the provider. In practice, this may not be available in all situations. The problem becomes one of POMDP with unknown transition probabilities. Such formulations are beyond the scope of this chapter. Algorithms for POMDP with unknown model exist in the literature [49] and are applicable to our problem.

3.3.1 A POMDP Formulation

To maximize his total gain, the provider decides the amount of bandwidth to lease to satisfy the users demand. Then, we suppose that the action space is composed of the following actions: to lease bandwidth to serve all users or to lease bandwidth to serve just users that have a good channel quality. Let denote by $a(t)$ the action of the provider at time slot t .

$$a(t) = \begin{cases} W_m, & \text{lease bandwidth to serve users with high channel quality;} \\ W_N, & \text{lease bandwidth to serve all users;} \\ 0, & \text{No leasing.} \end{cases}$$

where m is the number of users with a good channel.

At the beginning of each time slot t , the true system state $s_t \in S$ is hidden from the provider. Let Θ be the set of all observations. An observation $\theta_t \in \Theta = \{o_1(t), o_2(t), \dots, o_N(t)\}$ can be seen by the provider at time t . The observation θ_t is the set of decisions of each user, where $o_i(t) = \{0(\text{refuses}), h_i(\text{accepts})\}$. $o_i(t) = h_i$ if the user decides to use the service, then the provider observes his fading channel, and $o_i(t) = 0$ if the user decides to not transmit at time slot t . A user i accepts the service if $u_i \geq 0$ (equation 3.1). The channel state is modeled by a time-homogenous discrete Markov process.

As the system is partially observable, the internal state of the Markov process is unknown. At the beginning of slot t , our knowledge of the internal state of the network based on all past decisions and observations can be summarized by a belief vector. The provider has a belief vector $\Lambda(t) = [\lambda_1(t), \lambda_2(t), \dots, \lambda_N(t)]$ where $\lambda_i(t)$ is the probability on the channel state of user i at the beginning of slot t prior to the state transition and given the decision and observation history. This conditional probability is updated at each time slot depending on the observation. We denote by $\Omega(\cdot|\Theta(t))$ the update rule operator on the belief vector. It has been proved in [47] that this belief vector gives sufficient statistics for the design of the optimal action at time slot t . The update rules of the belief vector of each user i are given by :

$$\lambda_i(t+1) = \Omega(\lambda_i(t)|\Theta(t))$$

where

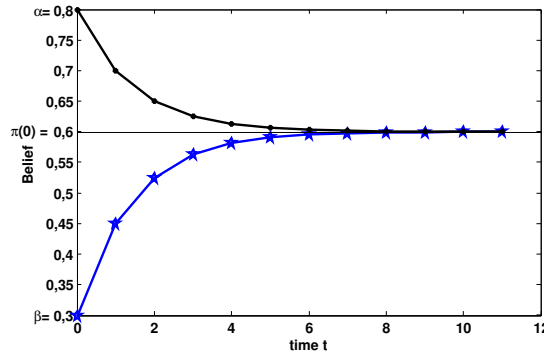
$$\Omega(\lambda_i(t)|\Theta(t)) = \begin{cases} \alpha & \text{if } o_i(t) = h_H; \\ \beta & \text{if } o_i(t) = h_L; \\ \lambda_i(t)(\alpha - \beta) + \beta & \text{if } o_i(t) = 0. \end{cases}$$

Every time slot $o_i(t) = 0$ repeats itself, the information of the provider about the real channel state of user i is further from reality. $\Omega(\lambda_i(t)|\Theta(t))$ in this case is either a decreasing or increasing function depending on the initial belief $\lambda_i(0)$. Let $\pi(0)$ be the stationary probability on the channel state of a user. The function $\Omega(\lambda_i(t)|\Theta(t))$ converges to the steady state $\pi(0)$. Then $\Omega(\pi(0)) = \pi(0)$, and

$$\pi(0) = \frac{\beta}{1 - \alpha + \beta}$$

Figure 3.1 represents an illustrative diagram of the values of $\Omega(\lambda_i(t)|\Theta(t))$ over time when $o_i(t) = 0$ in the case where $\alpha > \beta$.

Reward: When there is m users with good channel, the provider receives an instantaneous reward $r(a, t)$ as a result of choosing action a at time slot t . A natural definition of the reward function is the total revenue of the provider after leasing the optimal amount

FIGURE 3.1: Evolution of $\lambda(t)$ over time for $o(t) = 0$.

of bandwidth.

$$r(a, t) = \begin{cases} 0 & \text{if } a(t) = 0; \\ mC_F - C_W W_m & \text{if } a(t) = W_m; \\ NC_F - C_W W_N & \text{if } a(t) = W_N. \end{cases}$$

where W_N is the solution of

$$\frac{W_N}{N} \ln \left(1 + \frac{h_L P}{(W_N/N)\sigma^2} \right) = C_F$$

and W_m the solution of

$$\frac{W_m}{m} \ln \left(1 + \frac{h_H P}{(W_m/m)\sigma^2} \right) = C_F.$$

As m is unknown, the provider is based on his belief vector to compute the number of users that could have a good channel at the next slot. Let $P(K = m)$ be the probability that m users have a good channel. We have

$$\begin{cases} P(K = 0) = \prod_{i=1}^N (1 - \lambda_i); \\ P(K = 1) = \sum_{i=1}^N \lambda_i \prod_{j=1, j \neq i}^N (1 - \lambda_j); \\ \dots \\ P(K = N) = \prod_{i=1}^N \lambda_i. \end{cases}$$

Therefore the instantaneous reward is a result of choosing action a and given the belief Λ at a time t . We denote this reward by $r(a, \Lambda, t)$. Then, the payoff of the provider is

given by

$$r(a, \Lambda, t) = \sum_{m=1}^N P(K = m) \times \begin{cases} 0 & \text{if } a(t) = 0; \\ mC_F - C_W W_m & \text{if } a(t) = W_m; \\ NC_F - C_W W_N & \text{if } a(t) = W_N. \end{cases}$$

At each time slot, the decisions are made by the provider. We consider a discount reward criterion. Moreover, we do not restrict our horizon to a time limit which is difficult to justify in practice. Our objective is then to find an optimal stationary policy which maximizes the expected long-term reward.

3.3.2 Optimal Bandwidth Strategy

The sequence of operations in each time slot is depicted in figure 3.2. Let π be the policy

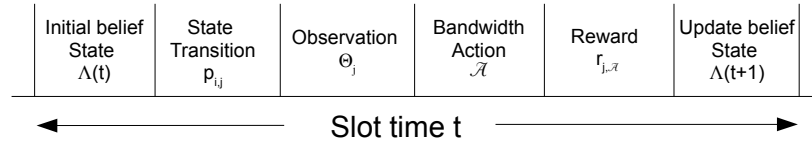


FIGURE 3.2: The sequence of operations in our POMDP in a time slot

that the provider will use. A policy π for our POMDP is thus given by a set of functions, each mapping from the current belief vector $\Lambda(t)$ to the bandwidth actions set \mathcal{A} to be taken in slot t . A policy π can be characterized by a value function V^π which is defined as the expected future discounted reward $V^\pi(\Lambda)$ the provider can gather by following π starting from belief Λ :

$$V^\pi(\Lambda) = \mathbb{E}_\pi \left[\sum_{t=1}^{\infty} \gamma^t r(a, \Lambda, t) | \Lambda(1) = \Lambda \right] \quad (3.15)$$

where \mathbb{E}_π represents the conditional expectation given that policy π is employed, $\Lambda(1)$ the initial belief vector which can be an arbitrary distribution, and γ is a discount rate, $0 \leq \gamma < 1$. The discount rate ensures a finite sum and is usually chosen close to 1. A policy π which maximizes V^π is called an optimal policy π^* ; it specifies for each belief Λ the optimal action to execute at the current step. Employing π^* , the provider will maximize his total revenue.

3.4 Numerical Examples

Our objective in this section is to validate the performance of the suggested model through basic experiments. Specifically, we are interested in examining how close we get in practice to the desired operating point (i.e. the optimal number of users). We start by describing the setup used for the experiments. We consider a mobile virtual network operator that can serve simultaneously fifty users $N = 50$. The induced applied power is decreasing from a user to another as follows : $h_1 P_1 = 5$ and $h_{i+1} P_{i+1} = h_i P_i / 1,05$. We suppose that the provider charges users with a cost $C_F = 1$, and lease bandwidth from authority with a price $C_W = 0.1$ per unit bandwidth. We next examine the evolution of the number of users and the profit of the provider in time.

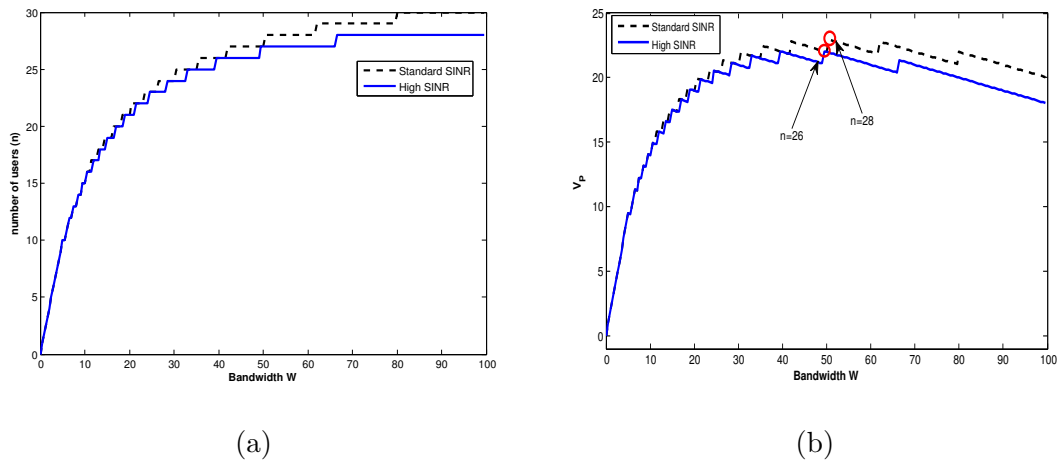


FIGURE 3.3: The number of users and the revenue of the provider vs. the bandwidth W without interference

Figure 3.3(a) shows the evolution of the number of users with increasing the bandwidth W for standard and high SINR without interference. The number of users that accept the service is an increasing step curve. We observe that n does not reach the value of N even if there is enough bandwidth (the maximal value of n is $n = 30$). This behavior is the result of the payoff condition of users. Indeed, while the condition $u_i \geq 0$ is satisfied, the user i accepts the service.

In figure 3.3(b) we plot the revenue of the provider while increasing the leased bandwidth. When the reserved bandwidth is low, the approximation with high SINR gives the same result as the original problem. the curves reach the maximal values which corresponds to the optimal number of users the provider has to accept to maximize his profit. The provider has no interest to lease more bandwidth because users will refuse the service. The profit starts decreasing after that. The optimal number of users in standard SINR is $n = 28$, whereas in high SINR is $n = 26$. This is a near-optimal solution that allow

us to approach the maximal profit ($V_P = 22.7$ and the approximation in high SINR is $V_P = 21.4$).

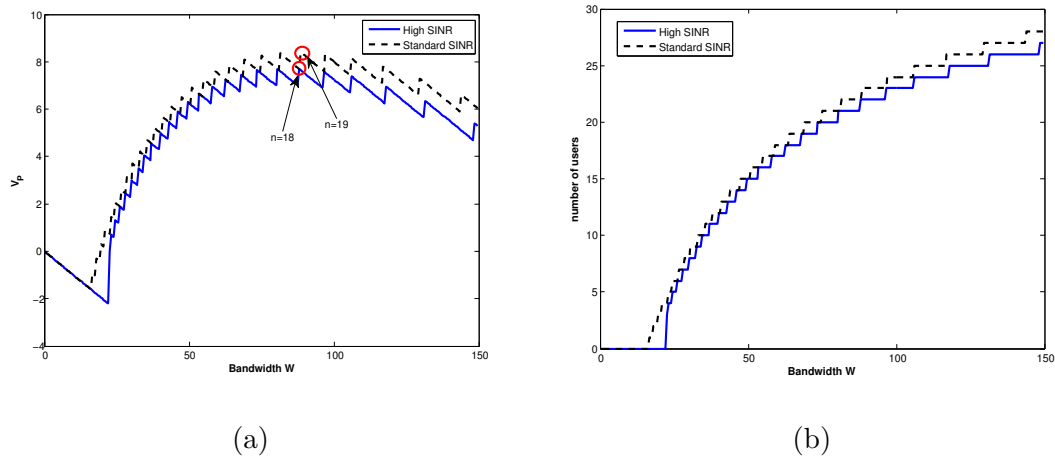


FIGURE 3.4: The number of users and the revenue of the provider vs. the bandwidth W with interference

When interference between users is included in the model (Figure 3.4), the provider has a threshold to exceed in term of bandwidth if he wants that users accept to pay for the service. In fact, for low leased bandwidth the interference is high and the quality of service is poor. In figure 3.4(b) the number of users increases after the value $W \simeq 23$, which influence on the providers' profit in figure 3.4 (a). We notice that the optimal number of users and consequently the profit of the provider are less than the case without interference ($n = 19$ rather than $n = 28$), which is somehow realistic since interference influence on the overall performance.

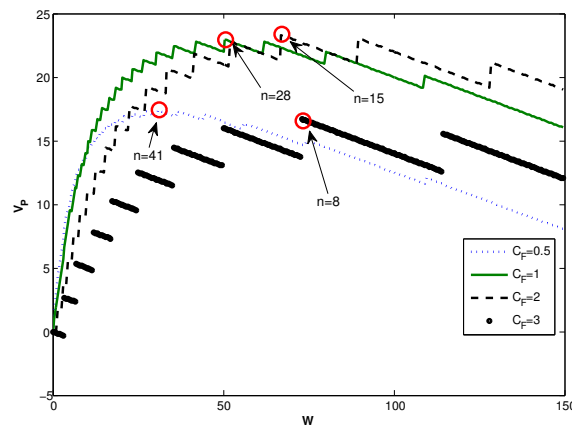


FIGURE 3.5: Impact of the cost C_F on the profit

In figure 3.5 we plot the impact of the price fixed by the provider on his revenue. The higher the cost is, the lower the optimal number of users becomes. This would not necessarily mean that the revenue decrease with the cost. Indeed, the provider can earn more with a higher price, even if the optimal number of users accepted by the provider

is much less (with $C_F = 2$ the number of users is $n = 15$, and with $C_F = 1$ we obtain $n = 28$). We can conclude that the provider has to find a trade off between the pricing scheme and the number of users to serve simultaneously.

In a dynamic environment the provider determines at each time slot if he has to serve only users with high quality channel rather than all users. In figure 3.6 and 3.7, we illustrate the optimal strategy of the provider using the POMDP framework described in section 3.3. Since the problem is multidimensional, we plot for illustrative purpose simple cases of 2 and 6 users served by the provider (i.e. $N = 2$ and $N = 6$). We denote the strategies of the provider as follows. We refer to the strategy of accepting all users in figures by '0' and accepting i users with good channel state by 'i'. To study the effect of initialization, we plot three scenarios with different values of belief representing the maximum (α), the minimum (β), and a middle value ($\Omega(\lambda)$) of the belief probability. We take $\alpha = 0.8$, $\Omega(\lambda) = (\alpha^2 - \alpha\beta + \beta)(\alpha - \beta) + \beta$ and $\beta = 0.1$, which means the scenarios where the probability to have a good channel is high. We plot in figure 3.6 the case of two users. In figure 3.7 we study the case of multiusers ($N = 6$) and we show the decisions of the provider when the belief of users increase. From figure 3.7(b) and (c), the only case where the provider chooses to accept all users (which means action '0'), is when all users have a bad channel. Otherwise, the provider earns more by accepting users with good channel as the belief gets closer to α .

3.5 Conclusion

We have considered in this chapter the revenue maximization problem in a MVNO with self-interested wireless users. We introduce a model with flat fee. Based on his utility function, each user decides to buy the service or not. A model without interference where the provider supplies different bandwidth frequencies to different users is first considered, then extended to support interference between users. In both cases, the optimal amount of bandwidth the provider has to lease is derived. A near-optimal solution is proposed with respect to users strategy, interference and bandwidth management. We propose a more general model using a POMDP framework to illustrate the case where the provider doesn't have complete information about the channel state of all users. We find the optimal policy the provider has to follow to maximize his revenue based on a belief vector. Through simulations we show that increasing the flat fee for access to the network service, can significantly decrease the number of active users, but not necessarily decreasing the total profit of the provider. Interference and network congestion can play a crucial rule in degrading the QoS offered to end-users. the provider has to find a trade off between pricing scheme and the offered QoS. The scope of our work may be extended

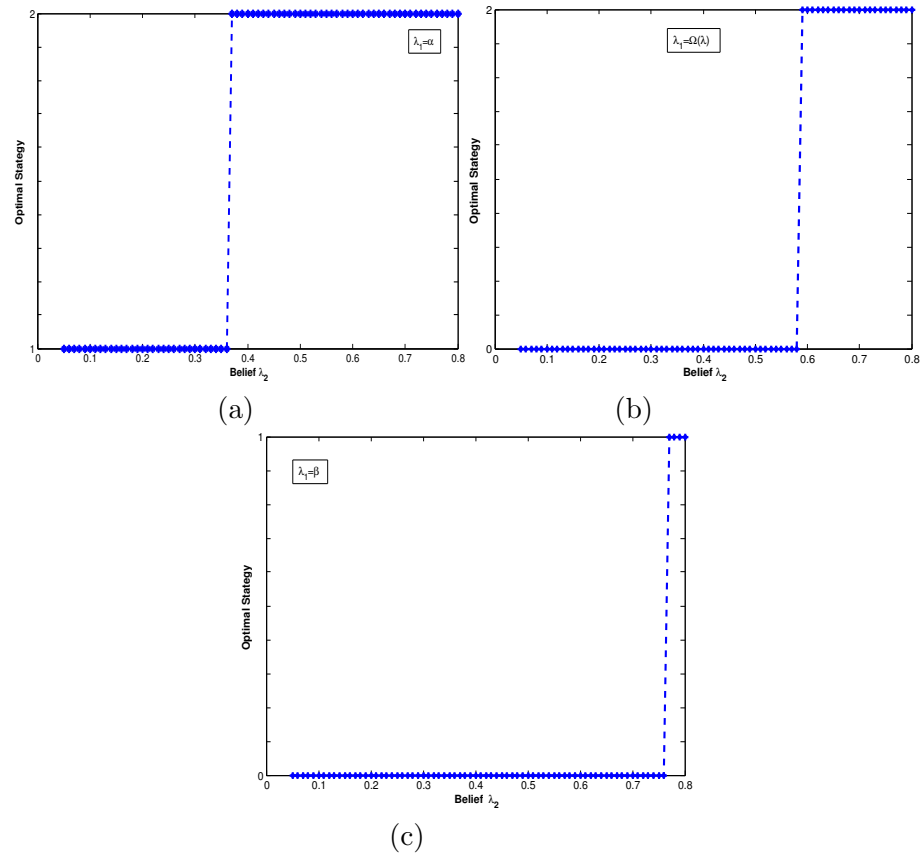


FIGURE 3.6: The optimal Strategy employed by the provider with 2 users, $\alpha = 0.8$ and $\beta = 0.05$

in several respects. In the network pricing context, we can consider the case where the system is restricted to setting a user price for power usage. A challenging direction is to consider competition between several providers in a game theoretical aspect with selfish users.

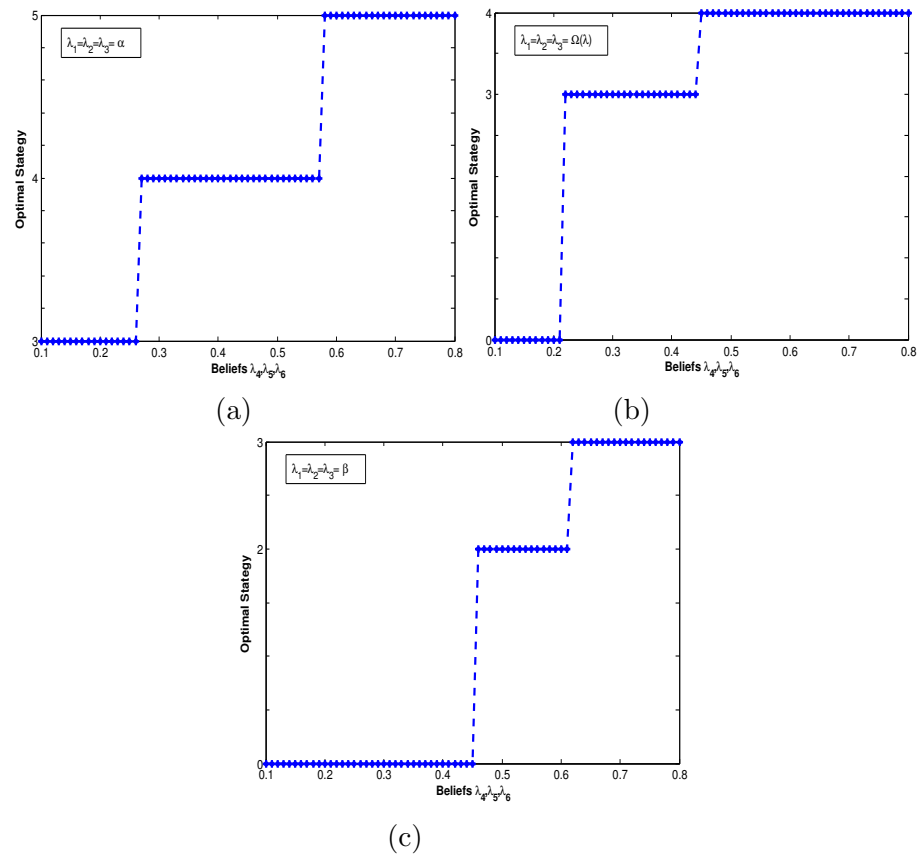


FIGURE 3.7: The optimal Strategy employed by the provider with 6 users, $\alpha = 0.8$ and $\beta = 0.1$

Part II

Optimal Control and Self Organized users in Delay Tolerant Networks

Chapter 4

Stochastic aging control and games for smartphones in delay tolerant networks

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4.1 Introduction

The demand for Internet services that require frequent updates through small messages has tremendously grown in the past few years. While the popularity of traditional applications of that kind, such as weather forecasts, traffic reports and news, is unlike to decline, novel applications, such as Twitter, have arisen. Twitter, alone, recorded a 1,500% increase in the number of registered users since 2006, and currently counts with more than 100 million users worldwide. For a second example, mobile messaging with

Exchange ActiveSync [50] allows smartphone users to receive timely updates when new data items arrive in their mailboxes. Today, Exchange ActiveSync is supported by more than 300 million mobile devices worldwide. Henceforth, for the sake of concreteness we focus on microblogging applications, such as Twitter or similar news feeds.

Users of microblogging applications join interest groups and aim at receiving small messages from editors. As messages age, they get outdated and their utilities decrease. As a consequence, users must control when to receive updates. A user willing to receive an update activates his mobile device, which then broadcasts periodic beacons to inform demands to service providers.

Although the use of microblogging applications by domestic users is usually free, their access from mobile devices consumes energy from limited batteries and is subject to fees. We consider users that can access the Internet either through a WiFi or 3G network. The 3G network provides broader coverage, but its usage requires a subscription to a cell phone data plan. More generally, our results apply to any scenario in which users can access the network through multiple interfaces with different costs and ubiquitousness [51, 52].

Let the *age* of a message held by a user be the duration of the interval of time since the message was downloaded by such user. If a user activates his mobile device and is in the range of a service provider (WiFi access point or 3G antenna), an update is received and the age of the message held by the user is reset to one, at the expense of the previously mentioned monetary and energy costs. Thus, users face a tradeoff between energy and monetary costs and their messages aging. To cope with such a tradeoff, users decide, based on the age of the stored message, whether to activate the mobile device, and if so, which technology to use (WiFi or 3G). We refer to a policy which determines activation decisions as a function of message ages as an *aging control policy*.

We propose a model that computes the optimal aging control policy. The model accounts for energy costs, prices and the utility of messages as a function of their age. We show that users can maximize their utilities by adopting a simple threshold policy. The policy consists of activating the mobile device if the content age surpasses a given threshold and remaining inactive otherwise. We derive properties of the optimal threshold, and a closed-form expression for the average reward obtained by users as a function of the selected strategies. Then, we study the game problem in which the content providers (publishers) offer bonus packages to mobile users, so as to motivate them to download updates through the WiFi network. The bonus provides a natural and equitable incentive for mobile users to adapt their policy according to the WiFi network condition. By reducing the bonus, providers incentivize users to decrease their download rates during congestion times. Using the dynamic programming techniques, we characterize threshold

type Nash equilibrium strategies, namely strategies in which a mobile remains inactive (resp., active) if the age of its message is below (resp., above) a given threshold. The mobile randomizes between active and inactive when the age of its message equals the threshold. Finally, we show the accuracy of our approach using traces collected from the UMass DieselNet bus network.

The remainder of this chapter is organized as follows. We start by related works in §4.2. After further discussing the need for aging control, in §4.4 we present our model, and in §4.5 we report results obtained with traces from the UMass DieselNet bus network. Our model analysis is shown in §4.6, followed by the solution of the publishers problem in §4.7. We present a discussion of our modeling assumptions in §4.9, and §4.10 concludes.

4.2 Related Work

The literature on measuring [53–55], modeling [56–60] and control [61–64] in wireless networks is vast. Nevertheless, we were not able to find any previous study on the *aging control* problem as described in this chapter. Previous work accounted for the modeling of aging [56] or for the age control by publishers [61, 63], but not for users aging control.

Chaintreau *et al.* [56] model the distribution of message ages in a large scale mobile network using a spatial mean field approach. Their model allows the analysis of gossiping through opportunistic contacts. In this work, in contrast, we assume that nodes rely exclusively on base stations and access points in order to receive their updates.

Activation control strategies were proposed in [61, 62, 65, 66]. In [61] the authors consider publishers of evolving files, that aim at reducing their energy expenditure by controlling the probability of transmitting messages to users. In [62], a joint activation and transmission control policy is proposed so as to maximize the throughput of users under energy constraints. In [66], a joint activation and link selection control policy is proposed so as to minimize the energy consumption under delay constraints. Our work differs from [61, 62, 66] in two ways as 1) we investigate the activation policy of mobile nodes based on the utility of their messages and 2) we study the publishers bonus strategy. In addition, our analysis is carried out using MDPs and is validated using UMass Dieselnet traces.

The utility function introduced in this chapter corresponds to the impatience function presented by Reich and Chaintreau [63]. Reich and Chaintreau study the implications of delays between requests and services on optimal content replication schemes. If users have limited caches and cannot download all the requested files every time they are in

range of an access point, the insights provided by [63, 67] need to be coupled with the ones presented here in order to devise the optimal joint activation-replication strategy. Therefore, aging control, as described here, significantly complements replication control, as described in [63, 67].

4.3 Why Aging Control?

The goal of an aging control policy is to provide high quality of service while 1) reducing energy consumption and 2) reducing 3G usage, by leveraging WiFi connectivity when available. Whereas the reduction in energy consumption is of interest mainly to subscribers, the reduction in 3G usage is of interest both to service providers and subscribers. Next, we discuss a few issues related to the adoption of aging control from the service providers and subscribers standpoints.

4.3.1 Service Provider Standpoint: Limited Spectrum

The increasing demand for mobile Internet access is creating pressure on the service providers, whose limited spectrum might not be sufficient to cope with the demand [51, 68]. To deal with such pressure, some wireless providers are offering incentives to subscribers to reduce their 3G usage by switching to WiFi [69]. Therefore, it is to the best interest of the service providers to devise efficient aging control policies for their users. Aging control policies can not only reduce the pressure on the 3G spectrum, but also reduce the costs to service providers that support hybrid 3G/WiFi networks (with savings of up to 60% against providers that offer only 3G [51]).

4.3.2 Users Standpoint: Energy Consumption, Monetary Costs and Coverage

4.3.2.1 Energy consumption and AP scanning

The energy efficiency of WiFi and 3G radios differs significantly. WiFi users actively scan for APs by broadcasting probes and waiting for beacons sent by the APs. If multiple beacons are received, users connect to the AP with the highest signal strength. The association overhead, incurred when searching and connecting to the APs, yields substantial energy costs. Niranjan *et al.* [70] report that the energy consumption of a WiFi AP scan is 0.63J in Android G1 and 1.18J in Nokia N95, taking roughly 1 and 2 seconds, respectively (note that in one time slot users might perform multiple AP

scans). To simplify presentation, we consider only the energy costs related to association overhead. In many scenarios of practical interest WiFi and 3G radios incur comparable energy costs after the handshaking phase, and our model can be easily adapted to account for cases in which such energy costs differ.

4.3.2.2 Monetary costs

Whereas free WiFi hotspots are gaining popularity, the use of 3G is associated to monetary costs. For example, in the United States most companies are ending their unlimited data plans [71]. Subscribers incur a cost which goes up to 0.10 USD per megabyte after exceeding their monthly quota.

4.3.2.3 Coverage

It is well known that the coverage of 3G is much broader than the coverage of WiFi. This is because the 3G towers are placed by operators so as to achieve almost perfect coverage, while WiFi access points are distributed and activated in an ad hoc fashion. For instance, it has been reported in [51] that 3G and WiFi are available roughly 12% and 90% of the time in the town of Amherst, Massachusetts.

4.3.2.4 Approximations

In light of the above observations, in the rest of this chapter, except otherwise stated, we consider the following three approximations concerning energy consumption, monetary costs, and coverage. We assume that 1) the energy consumption of scanning for WiFi access points dominates the energy costs of the 3G and WiFi radios and 2) WiFi is intermittently available whereas 3G offers perfect coverage. Note that the above approximations are made solely to simplify presentation: our model has flexibility to account for different energy consumption and monetary costs of WiFi and 3G, and can be easily adapted to account for a 3G network that does not have perfect coverage. More generally, our work extends to any setup where users access a hybrid network and face monetary, energy and coverage tradeoffs when deciding which infrastructure to use.

4.3.3 Adopting Aging Control

Next, we discuss two key aspects pertaining the adoption of aging control: 1) the delay tolerance of the applications and 2) the availability of WiFi access points.

4.3.3.1 Delay Tolerant Applications, Age and Utility

Aging control is useful for applications that can tolerate delays, such as news feeds and email. For these applications, users might be willing to tolerate some delay if that translates into reduced energy consumption or monetary costs.

How does the utility of a content degrade with its age? The answer to this question is user and application dependent. It turns out that some applications, such as JuiceDefender [72], already allow smartphones users to specify their delay tolerance per application so as to save battery. For instance, users can simply specify a delay threshold, after which they wish to have received an update. In our model, this corresponds to a utility that has the shape of a step function [73].

4.3.3.2 WiFi Access Points

Open WiFi access points are widespread. The age control mechanisms described in this chapter can rely on such access points, which users encounter in an ad hoc fashion. Alternatively, Internet service providers can deploy their own closed networks of WiFi access points, in order to alleviate the load of their 3G networks. In France, enterprises such as SFR and Neuf are already adopting such strategy. The age control mechanisms presented here can be applied in this setting as well. In this case, users are required to perform a web-based login in order to access the WiFi spots. Note that even if mobile users have perfect geographic information about the location of the access points, random factors like attenuation (fading) and user speed will determine the availability of the access points, which will vary temporally and spatially.

4.3.3.3 Markov Decision Processes

Remaining inactive at a given instant of time is particularly useful if future transmission opportunities are available in upcoming time slots. However, as discussed above, WiFi access points are intermittently available. Therefore, WiFi users experience a random delay between the instant of time at which they activate their devices and the instant at which they obtain content updates. How to account for the unpredictability of transmission opportunities in upcoming slots? To answer this question, in the next section we propose a model, based on a Markov Decision Process, which naturally accounts for the effect of the actions at a given time slot on the future states of the system, and allows us to derive the structure of the optimal aging control policy.

4.4 Aging Control Model

We consider mobile users that subscribe to receive content updates. In the microblogging jargon, such users are said *to follow* a content. Content is transmitted from publishers to users, through messages sent by service providers. The *age* of the message held by a user is defined as the length of time, measured in time slots, since the message was downloaded. Note that we assume that updates are available at every time slot with high probability (see §4.9).

Let x_t be the age of the message held by a user at time t . The age of the message equals one when the user first receives it, and increases by one every time slot, except when the user obtains an update, time at which the age is reset to one.

A user can receive message updates when his mobile device is in range of a service provider and the contact between them lasts for a minimum amount time which characterizes a *useful contact opportunity*. While the 3G technology is assumed to guarantee perfect coverage, WiFi users are subject to outages. Let e_t be an indicator random variable equal to 1 if there is a useful contact opportunity with a WiFi provider at time t , and 0 otherwise. We let $q = E[e_t]$ and assume $0 < q < 1$. Next, we state our key modeling assumption.

Assumption 1. Uniform and independent contact opportunity distribution: The probability of a useful contact opportunity between a user and WiFi providers is constant and independent across time slots, and equals q .

Under Assumption 1, there are no correlations in time between contact opportunities experienced by a user; this is a strong assumption, since such correlations are present in any mobile network. However, as shown in §4.5.1, there are scenarios of practical interest in which the uniformity and independence assumption does not compromise the accuracy of the results obtained using our model. Therefore, we proceed our analysis under such an assumption, indicating its implications and studying scenarios that are out of the scope of our model using real-world traces.

The goal of each user is to minimize the expected age of the content he follows, accounting for energy and monetary costs. In order to achieve such goal, users must choose at each time slot t their actions, a_t . The available actions are

$$a_t = \begin{cases} 0, & \text{stay inactive} \\ 1, & \text{use WiFi} \\ 2, & \text{use WiFi if a useful contact opportunity exists, else use 3G} \end{cases}$$

The age of the content followed by a user increases by one if his device is inactive or if it is not in range of a service provider, and is reset to one otherwise. Let M be the maximum age of a content. Then,

$$x_{t+1} = \begin{cases} \min(x_t + 1, M), & \text{if } (a_t=0) \text{ or } (a_t=1 \text{ and } e_t=0) \\ 1, & \text{if } (a_t=2) \text{ or } (a_t=1 \text{ and } e_t=1) \end{cases} \quad (4.1)$$

Let $U(x_t)$ be the utility of the followed content at time t . We assume that $U(x_t)$ is a non-increasing function of x , which corresponds to messages that become obsolete with time, and that $U(x_t) = Z$ if $x \geq M$.

Let G be the cost incurred to maintain the mobile device active, measured in monetary units. Then, the energy cost c_t is given as a function of a_t as

$$c_t(a_t) = \begin{cases} G, & \text{if } a_t \geq 1 \\ 0, & \text{if } a_t = 0 \end{cases} \quad (4.2)$$

Service providers charge a price for each message transmitted. The prices charged by WiFi and 3G providers are P and P_{3G} , respectively. Note that the model includes the case where WiFi access points are open, and their access is free (i.e $P = 0$). When a user receives an update, he is subject to a monetary cost of m_t ,

$$m_t(a_t, e_t) = \begin{cases} P_{3G}, & \text{if } a_t = 2 \text{ and } e_t = 0 \\ P, & \text{if } a_t = 1 \text{ and } e_t = 1 \end{cases} \quad (4.3)$$

Let r_t be the instantaneous reward a user receives at time t , then we have

$$r_t(x_t, a_t) = U(x_t) - c_t(a_t) - m_t \quad (4.4)$$

The strategy of a user is given by the probability of choosing a given action a_t at each of the possible states. Without loss of generality, we restrict to Markovian stationary policies [74, Chapter 8]. The probability of choosing action a_t at state x_t is denoted by $\mu(a_t|x_t)$.

Problem Definition The problem faced by each user consists of finding the strategy μ that maximizes his expected average reward. the maximization problem is defined by

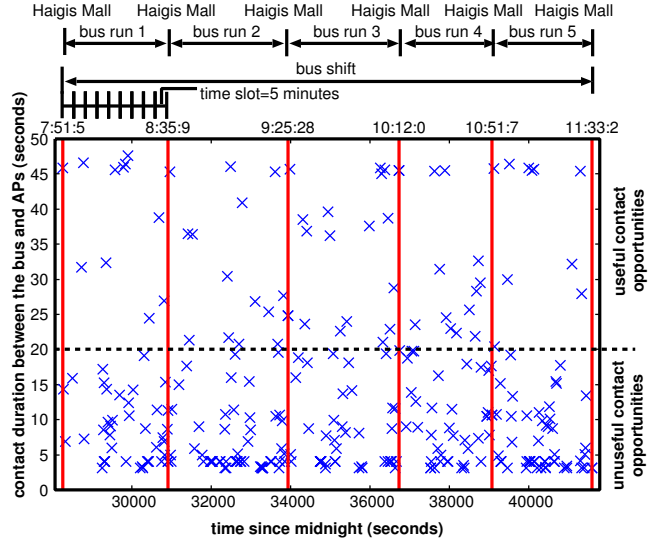


FIGURE 4.1: Bus-AP contacts during a typical bus shift.

USER PROBLEM: maximize $E[r; \mu]$, where

$$E[r; \mu] = \lim_{\ell \rightarrow \infty} \frac{1}{\ell} \sum_{t=0}^{\ell} E[r_t(x_t, a_t); \mu] \quad (4.5)$$

In what follows, we drop the subscript t from variables when analyzing the system in steady state.

4.5 Evaluating Aging Control Policies in DieselNet

In this section we use traces collected from the UMass Amherst DieselNet [53] to evaluate how aging control policies perform in practice. Our goals are 1) to show the accuracy of our model predictions and 2) to assess the optimality of the model predictions in the class of threshold policies.

The users of the microblogging application considered in this section are passengers and drivers of buses. We assume that users are interested in following a heavy load news feeds, for which updates are issued every minute with high probability. Time is divided into slots of 5 minutes.

4.5.1 Methodology and Reference Configuration

We begin by describing our methodology and reference configuration, and then proceed to study the optimal policies. We assume that users do not have a cell phone data plan ($P_{3G} \rightarrow \infty$) and WiFi is free ($P = 0$).

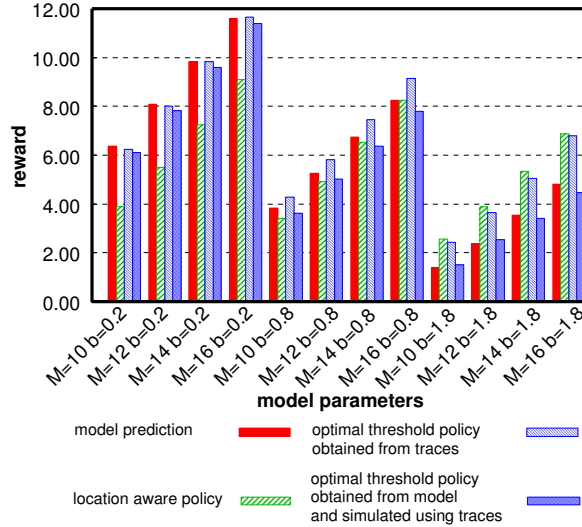


FIGURE 4.2: Rewards as predicted by our model and observed in DieselNet.

The computation of the optimal policy using the proposed model requires estimates of q , $U(x)$ and G . For a given bus shift, q is estimated as the number of useful slots in that shift divided by the total number of slots. Note that to compute the optimal strategy using our model we assume knowledge of q , but not of the distribution of contact times and durations. When searching for the optimal threshold strategy using traces, in contrast, we perform trace-driven simulations. For each bus shift, our simulator takes as input the string of ones and zeros corresponding to useful and unuseful slots, and computes the reward experienced by a user adopting a given activation policy. The strategy that yields the highest reward correspond to the *optimal trace-driven policy*.

In our reference setting, the utility of messages decays linearly during a bus run, and remains zero afterwards, $U(x) = \max(M - x, 0)$. Typical bus run durations vary between 40 minutes and 1 hour and 20 minutes. Therefore, We vary M between 10 and 16 (which correspond to 50 and 80 minutes, respectively), in increments of 2. For ease of presentation, let b be the energy cost scaled by a factor of $1/(M - 1)$,

$$b = G/(M - 1) \quad (4.6)$$

We vary b according to our experimental goals between 0.2, 0.8 and 1.8, corresponding to small, medium and high costs, respectively.

4.5.2 Optimal Policies

Next, we validate our model against traces assuming that users are restricted to threshold policies (non-threshold policies are considered in the next section). Figure 4.2 shows, for different model parameters, the averages of 1) the optimal reward *predicted* by our

model, 2) the reward *effectively obtained* using the optimal strategy computed by the model as input to our trace-driven simulator and 3) the *optimal trace-driven (threshold) policy*, with the 95% confidence intervals (to increase the number of samples, each bus shift is replayed 40 times).

In Figure 4.2, note that across all parameters, the rewards predicted by our model match the rewards effectively obtained using the policy proposed by our model pretty well. When the energy cost is low ($b = 0.2$), our model predictions also closely match the optimal trace-driven policy. When the energy cost is medium ($b = 0.8$) the accuracy of the predictions of our model depends on the maximum age M . Recall that typical bus runs last between 40 minutes and 1 hour and 20 minutes, and that when a bus run is completed, a contact occurs with high probability (see Figure 4.1(a)). If the maximum age is 50 minutes ($M = 10$), the fact that our model does not capture the correlations among contacts between buses and APs does not play an important role. However, as M increases, strategically setting the policy to account for such correlations is relevant. Similar reasoning holds when $b = 1.8$.

Figure 4.3(a) shows the distribution of the distance between the optimal threshold using our model versus the optimal trace-driven policy, for different model parameters. In accordance to our previous observations, when $b = 0.2$, the distance between the optimal threshold and the one computed by our model is smaller than or equal to two in at least 60% of the bus shifts. The same holds when $b = 0.8$ and $M = 10$. When $M = 16$ and $b = 1.8$, in contrast, the distance to the optimal threshold is smaller than two for less than 40% of the bus shifts.

Figure 4.3(b) reports the mode of the optimal threshold as estimated by our trace-driven simulator and by our model. The mode of the optimal threshold increases with the energy cost (see Proposition 4.9), and the distance between the simulator and model predictions never surpasses two.

Figure 4.3(c) provides further insight on the problem when $b = 1.8$. Until this point, we allowed different bus shifts to correspond to different threshold policies (i.e., we considered bus shift discriminated strategies). Next, we consider users that adopt the same threshold policy over all bus shifts (i.e., we consider flat strategies over bus shifts). For different threshold values, Figure 4.3(c) shows the average reward obtained using our trace-driven simulations (see Figure 4.2 for confidence intervals). Note that the optimal threshold equals eight in the four scenarios under consideration. This threshold value, in turn, is in agreement with the mode predicted by our model (see Figure 4.3(b)). In Figure 4.5 we reproduce the results of Figure 4.3(c) using our model. We let $q = 0.53$, the median contact probability (see Figure 4.4(c)). Comparing Figure 4.3(c) and Figure 4.5, we observe that the empirical curves are predicted by our model with remarkable

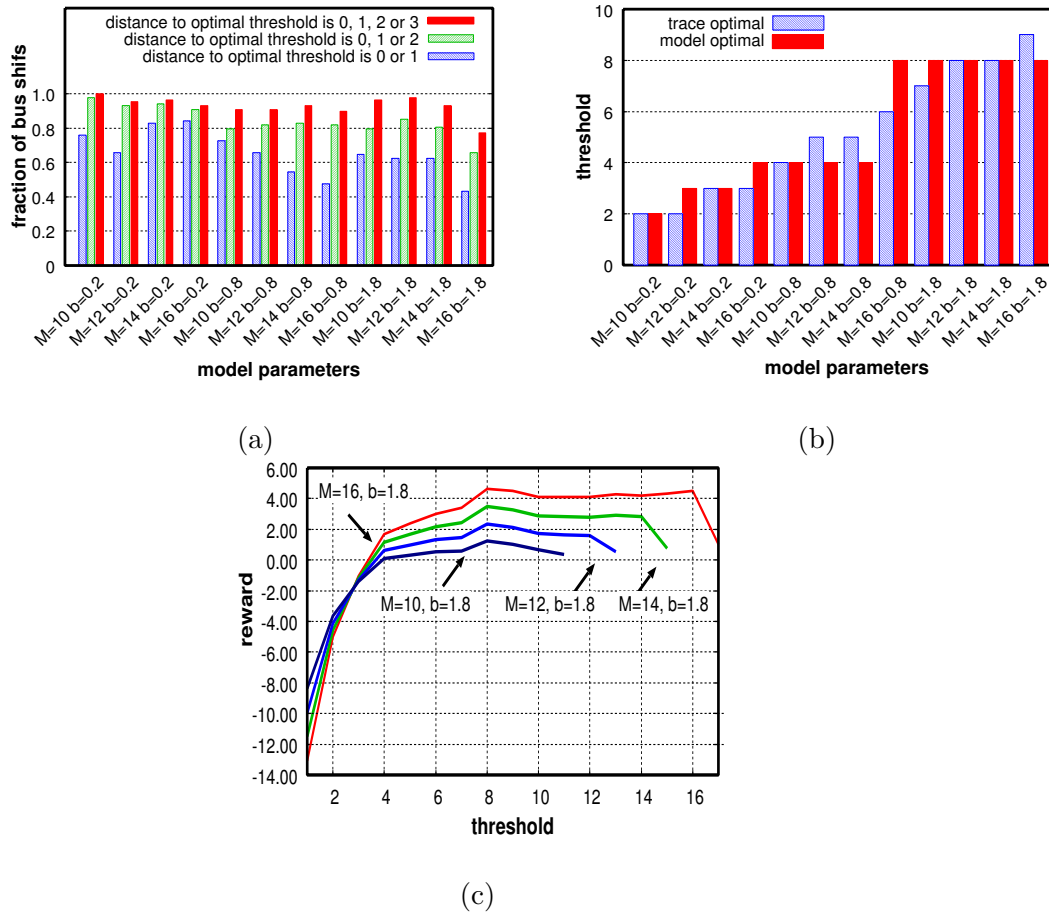


FIGURE 4.3: Model validation (a) distance between optimal trace-driven threshold and optimal model threshold; (b) optimal threshold mode; (c) trace-driven reward as a function of the threshold, where threshold is assumed the same at all bus shifts.

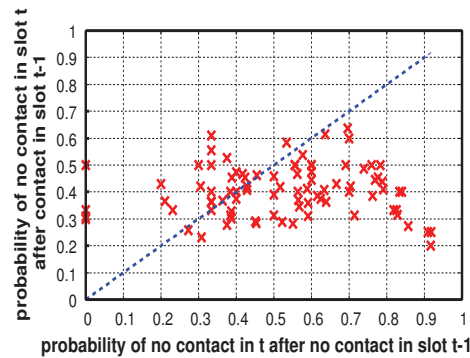


FIGURE 4.4: Useful contact opportunity statistics : scatter plot of opportunities in consecutive slots.

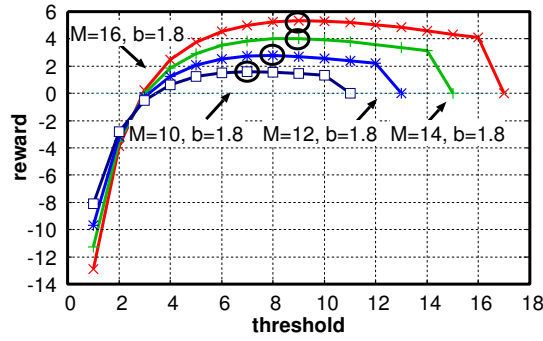


FIGURE 4.5: Model numerical evaluation ($U(x) = M - x$, $P = 0$, $q = 0.54$).

accuracy. The distance between the optimal threshold predicted by our model (marked with circles in Figure 4.5) and the one obtained through the trace-driven simulations (consistently equal to eight) is smaller than or equal to 1, and the utility discrepancy does not surpass 0.5.

4.6 Model Analysis

We introduce two special classes of policies, the *two-threshold policies* and the *threshold policies*. Let s and s_{3G} be the WiFi and the 3G thresholds respectively, $1 \leq s \leq s_{3G} \leq M + 1$. A policy which consists of setting $a = 0$ when $x < s$, $a = 1$ when $s \leq x < s_{3G}$, and $a = 2$ if $x \geq s_{3G}$, is referred to as a *two-threshold policy*. If users have no access to 3G ($P_{3G} \rightarrow \infty$), a policy which consists of backing off if $x < s$ and being active if $x \geq s$ is referred to as a *threshold policy*.

Note that while $x \in [1, M]$, the thresholds assume values in the range $[1, M + 1]$. When $P_{3G} \rightarrow \infty$, $s = M + 1$ means that the user should remain always inactive.

Our goals now are (a) to derive the optimality conditions that must be satisfied by the optimal policy and (b) to show properties of the optimal threshold. We tackle each of the goals in one of the subsequent sections, respectively. For ease of presentation, we will give in the upcoming sections the proofs of the case where ($P_{3G} \rightarrow \infty$). The other case is similar in spirit.

4.6.1 Optimal Policy General Structure

We now derive the general structure of the optimal policy. To this goal, consider a fixed policy μ . In this section we assume that, under μ , users have a positive activation probability in at least one state. The conditions for the optimality of the policy which consists of remaining always inactive will be established in Proposition 4.5.

variable	description	
a_t	action of user	
x_t	age of message	
r_t	reward	
e_t	=1 in case of useful contact opportunity, =0 otherwise	
parameter	description	determined by
$U(x)$	utility of message at age x	user
P_{3G}	price of 3G	3G service provider
P	price of WiFi	WiFi service provider
G	activation cost	
q	probability of useful contact opportunity, $q = E[e_t]$	

TABLE 4.1: Table of notation (subscripts dropped in steady state).

Let \mathcal{P}_μ denote the transition probability matrix of the Markov chain $\{x_t : t = 1, 2, \dots\}$ which characterizes the dynamics of the age, given policy μ . Let $r_\mu(x)$ be the expected instantaneous reward received in a time slot when the system is in state x and policy μ is used. The vector of expected instantaneous rewards is denoted by \mathbf{r}_μ .

Let the gain, g_μ , be the average reward per time slot in steady state, $g_\mu = E[r; \mu]$. Since the number of states in the system is finite, and from each state there is a positive probability of returning to state 1, \mathcal{P}_μ comprises a single connected component, and g_μ does not depend on the initial system state.

The *relative reward* of state x at time t , $V(x, t)$, is the difference between the expected total reward accumulated when the system starts in x and the expected total reward accumulated when the system starts in steady state. Let $V(x) = \lim_{\ell \rightarrow \infty} V(x, \ell) = \lim_{\ell \rightarrow \infty} \left(\sum_{t=0}^{\ell} \mathcal{P}_\mu^t (\mathbf{r}_\mu - g_\mu \mathbf{e}) \right) (x)$, where \mathbf{e} is a column vector with all its elements equal to one. It follows from (4.4) and similar arguments as to those in [74, eq. (8.4.2)] that a policy which satisfies the following conditions, for $1 \leq x \leq M$, is optimal,

$$V(x) = U(x) + \max \left(V(\min(x+1, M)) - g_\mu, \right. \\ \left. -G + q(V(1) - P) + (1-q)V(\min(x+1, M)) - g_\mu \right) \quad (4.7)$$

An optimal policy is obtained from the optimality conditions as follows,

$$a(x) = \begin{cases} 0, & \text{if } -G/q + (V(1) - P) \leq V(\min(x+1, M)) \\ 1, & \text{otherwise} \end{cases} \quad (4.8)$$

The existence of an optimal policy in the class of threshold policies follows from (4.8) and from the next subsection.

4.6.2 Optimal Threshold Policy

The following proposition reduces the problem of finding the optimal policy for the USER PROBLEM to the one of finding the two thresholds s and s_{3G} .

Proposition 4.1. *The USER PROBLEM admits an optimal threshold policy*

$$a(x) = \begin{cases} 0, & \text{if } x < s \\ 1, & \text{if } s \leq x \leq M. \end{cases} \quad (4.9)$$

Proposition 4.2. *The USER PROBLEM admits an optimal policy of two-threshold type such that*

$$\left. \begin{array}{l} \text{if } P_{3G} > G/q + P, \\ \\ a(x) = \begin{cases} 0, & \text{if } x < s \\ 1, & \text{if } s \leq x < s_{3G} \\ 2, & \text{otherwise} \end{cases} \end{array} \right\| \left. \begin{array}{l} \text{if } P_{3G} \leq G/q + P, \\ \\ a(x) = \begin{cases} 0, & \text{if } x < s_{3G} \\ 2, & \text{otherwise} \end{cases} \end{array} \right.$$

Proof of Proposition 4.1:

Let

$$H(x, 0) = U(x) + V(\min(x + 1, M)) \quad (4.10)$$

$$H(x, 1) = U(x) - G + q(V(1) - P) + (1 - q)V(\min(x + 1, M)) \quad (4.11)$$

It follows from (4.7)-(4.11) and [74] that the following policy is optimal, for $m = 1, \dots, M$,

$$a(m) = \begin{cases} 0, & \text{if } H(m, 0) \geq H(m, 1) \\ 1, & \text{otherwise} \end{cases} \quad (4.12)$$

At states M and $M - 1$, (4.7) implies that

$$\left\{ \begin{array}{l} (H(M, 0) \geq H(M, 1)) \wedge (H(M - 1, 0) \geq H(M - 1, 1)), \\ \quad \text{if } V(M) \geq U(M) - G + q(V(1) - P) + (1 - q)V(M) \\ (H(M, 0) \leq H(M, 1)) \wedge (H(M - 1, 0) \leq H(M - 1, 1)), \\ \quad \text{otherwise} \end{array} \right. \quad (4.13)$$

Equation (4.13) yields the following remark, used in the analysis of the base cases of the inductive arguments that follow.

Remark 4.3. $(H(M, 0) \geq H(M, 1)) \iff (H(M-1, 0) \geq H(M-1, 1))$.

We show that, for $m = 0, \dots, M-1$,

$$V(M-m-1) - V(M-m) \geq 0 \quad (4.14)$$

$$(H(M-m, 0) \geq H(M-m, 1)) \Rightarrow (H(M-m-1, 0) \geq H(M-m-1, 1)) \quad (4.15)$$

We consider two scenarios, $H(M, 0) \geq H(M, 1)$ and $H(M, 0) < H(M, 1)$.

- $H(M, 0) \geq H(M, 1)$

If H satisfies (4.15) then, from (4.7)-(4.11),

$$V(m) = U(m) + V(m+1), 1 \leq m \leq M-1 \quad (4.16)$$

and (4.14) holds.

Next, assume for the sake of contradiction that H does not satisfy (4.15). Let m be the largest state at which condition (4.15) is violated,

$$m = \max\{i | H(M-i, 0) \geq H(M-i, 1) \text{ and } H(M-i-1, 1) > H(M-i-1, 0)\} \quad (4.17)$$

It follows from (4.17) that

$$H(M-m-1, 1) > H(M-m-1, 0) \quad (4.18)$$

$$H(M-m+k, 0) \geq H(M-m+k, 1), k = 0, 1, \dots, m \quad (4.19)$$

(4.18) and (4.19) yield, respectively,

$$V(M-m) - V(1) < -G/q - P \quad (4.20)$$

$$V(M-k) - V(1) \geq -G/q - P, \quad k = 0, \dots, m-1 \quad (4.21)$$

Letting $k = m-1$ in (4.21),

$$V(M-m) = U(M-m) + V(M-m+1) \geq U(M-m) + V(1) - G/q - P \quad (4.22)$$

(4.20) and (4.22) yield the following contradiction

$$V(1) - G/q - P \leq V(M-m) < V(1) - G/q - P \quad (4.23)$$

Therefore, (4.15) holds for $m = 0, \dots, M-1$.

- $H(M, 0) < H(M, 1)$

Base case: We first show that $V(M-1) \geq V(M)$.

Note that $(H(M, 1) \geq H(M, 0)) \Rightarrow (H(M-1, 1) \geq H(M-1, 0))$ (see remark 4.3). It follows from (4.7) that

$$V(M-1) = U(M-1) - G - P + qV(1) + (1-q)V(M) - g_\mu \quad (4.24)$$

$$V(M) = U(M) - G - P + qV(1) + (1-q)V(M) - g_\mu \quad (4.25)$$

Hence, (4.24)-(4.25), together with the fact that $U(x)$ is non-increasing, yield $V(M-1) \geq V(M)$.

Induction hypothesis [assume result holds for $m < t$]: Assume that $V(M-m-1) - V(M-m) \geq 0$, for $m < t$, and $(H(M-m, 0) \geq H(M-m, 1)) \Rightarrow (H(M-m-1, 0) \geq H(M-m-1, 1))$, for $m < t$.

Induction step [show result holds for $m = t$]: Next, we show that $V(M-t-1) - V(M-t) \geq 0$ and that $(H(M-t, 0) \geq H(M-t, 1)) \Rightarrow (H(M-t-1, 0) \geq H(M-t-1, 1))$.

It follows from the induction hypothesis that $V(M-t+1) \leq V(M-t)$. We consider two cases,

i) $H(M-t, 0) \geq H(M-t, 1)$ The proof is similar to that of case 1.

ii) $H(M-t, 1) \geq H(M-t, 0)$ Now, we show that

$$V(M-t-1) - V(M-t) \geq 0.$$

Note that $(H(M-t, 0) \geq H(M-t, 1)) \Rightarrow (H(M-t-1, 0) \geq H(M-t-1, 1))$ holds vacuously. If $(H(M-t, 1) \geq H(M-t, 0))$ and $(H(M-t-1, 1) \geq H(M-t-1, 0))$,

$$\begin{aligned} V(M-t) + g_\mu &= U(M-t) - G - P + qV(1) \\ &+ (1-q)V(\min(M-t+1, M)) \end{aligned} \quad (4.26)$$

$$\begin{aligned} V(M-t-1) + g_\mu &= U(M-t-1) - G - P + qV(1) \\ &+ (1-q)V(\min(M-t, M)) \end{aligned} \quad (4.27)$$

Also, $V(M-t+1) \leq V(M-t)$ (induction hypothesis) and $U(M-t) < U(M-t-1)$ (by assumption). Hence, (4.27)-(4.28) yield $V(M-t) \leq V(M-t-1)$. ■

In Proposition 4.2, when the price charged by the 3G providers dominates the costs, the optimal policy consists of activating the WiFi radio if $s \leq x < s_{3G}$ and using the 3G

only if $x \geq s_{3G}$. If the price charged by the 3G providers is dominated by $G/q + P$, though, users are better off relying on the 3G technology, which offers perfect coverage.

To simplify presentation, in the upcoming sections we assume that the optimal threshold policy is unique. Given that the optimal policy μ is fully characterized by the threshold s , we let $E[r; s] = E[r; \mu]$. Next, we state the definition of the optimal threshold.

Definition 4.4. The threshold s^* of the optimal policy is

$$s^* = \operatorname{argmax}_s \{E[r; s]\} \quad (4.28)$$

Note that adding a constant to $U(x)$, $1 \leq x \leq M$, does not affect the optimal policy (4.8). Therefore, in the rest of this chapter we assume, without loss of generality, that $U(M) = 0$.

4.6.3 Optimal Threshold Properties

In this subsection we aim at finding properties of the optimal threshold. To this goal, we note that a user adopting a threshold strategy goes through cycles. Each cycle consists of an idle and active period. An idle period is initiated when the age is one, and ends immediately before the instant at which the age reaches the threshold s . At age s , an active period begins and lasts on average $1/q$ time slots, up to the instant at which the age is reset to one.

The following proposition establishes conditions according to which the optimal actions are invariant in time.

Proposition 4.5. *Invariant optimal actions:*

- *The optimal policy consists of being always active if and only if*

$$\frac{1}{1-q} \left(U(1) - q \sum_{x=1}^{M-1} U(x)(1-q)^{x-1} \right) \geq \frac{G}{q} + P \quad (4.29)$$

- *The optimal policy consists of being always inactive if and only if*

$$\sum_{j=1}^{M-1} U(M-j) \leq \frac{G}{q} + P \quad (4.30)$$

Proof. Let a be the optimal threshold policy.

- Conditions for the optimal policy to be always inactive :

It follows from the optimality conditions (4.7) that

$$a(x) = 0, 1 \leq x \leq M \iff H(x, 1) \leq H(x, 0), 1 \leq x \leq M \quad (4.31)$$

Therefore, from the above equation and (4.10)-(4.11),

$$a(x) = 0, 1 \leq x \leq M \iff V(1) - V(x) \leq G/q + P, 1 \leq x \leq M \quad (4.32)$$

Since $V(x)$ is decreasing (see Proposition 4.1), (4.32) yields

$$a(x) = 0, 1 \leq x \leq M \iff V(1) - V(M) \leq G/q + P \quad (4.33)$$

or equivalently,

$$a(x) = 0, 1 \leq x \leq M \iff V(M) \geq V(1) - G/q - P \quad (4.34)$$

From (4.7),

$$a(x) = 0, 1 \leq x \leq M \iff V(i) = U(i) + V(i + 1), 1 \leq i \leq M - 1 \quad (4.35)$$

where \Leftarrow in (4.35) follows from the assumption that there is a unique optimal policy that satisfies (4.7). Therefore,

$$a(x) = 0, 1 \leq x \leq M \iff V(j) = \sum_{i=j}^M U(i), j = 1, \dots, M \quad (4.36)$$

Finally, (4.34) and (4.36) yield

$$a(x) = 0, 1 \leq x \leq M \iff 0 \geq \sum_{i=1}^M U(i) - G/q - P \quad (4.37)$$

- Conditions for the optimal policy to be always active :

It follows from the optimality conditions (4.7) that

$$a(x) = 1, 1 \leq x \leq M \iff H(x, 1) \geq H(x, 0), 1 \leq x \leq M \quad (4.38)$$

Therefore, from the above equation and (4.10)-(4.11),

$$a(x) = 1, 1 \leq x \leq M \iff V(1) - V(x) \geq G/q + P, 1 \leq x \leq M \quad (4.39)$$

Since $V(x)$ is decreasing (see Proposition 4.1), it follows from (4.39) that

$$a(x) = 1, 1 \leq x \leq M \iff V(1) - V(2) \geq G/q + P \quad (4.40)$$

or equivalently,

$$a(x) = 1, 1 \leq x \leq M \iff V(2) < V(1) - G/q - P \quad (4.41)$$

Letting $x = 1$ in (4.7) yields

$$a(x) = 1, 1 \leq x \leq M \iff V(1) = -G + U(1) + qV(1) - qP + (1-q)V(2) - E[r; 1] \quad (4.42)$$

where \Leftarrow in (4.42) follows since our analysis is restricted to threshold policies. Note that $a(1) = 1$ is implied by the right hand side of (4.42) together with (4.7). If $a(1) = 1$ then $a(x) = 1, 1 \leq x \leq M$.

Finally, (4.41) and (4.42) yield

$$\begin{aligned} V(1) &= -G + U(1) + qV(1) - qP + (1-q)V(2) - E[r; 1] \iff \\ V(1) &\leq -G + U(1) + qV(1) - qP \\ &+ (1-q)(V(1) - G/q - P) - E[r; 1] \end{aligned} \quad (4.43)$$

The desired result follows from algebraic manipulation of (4.44),

$$a(x) = 1, 1 \leq x \leq M \iff E[r; 1] < U(1) - G/q - P \quad (4.44)$$

□

Remark 4.6. If the assumption of existence of one optimal threshold does not hold, the proof of Proposition 4.5 presented above remains valid after replacing all \iff by \Rightarrow .

Given that the condition for the optimal policy to be always inactive is established in the second part of Proposition 4.5, in what follows we focus on policies which consist of being active in at least one state.

For a fixed threshold policy with corresponding threshold s , let the system state transition probability matrix, \mathcal{P}_s , be

$$\mathcal{P}_s = \begin{matrix} 1 \\ \vdots \\ s \\ \vdots \\ M \end{matrix} \begin{bmatrix} 0 & 1 & & & & \\ 0 & 0 & 1 & & & \\ & & & \ddots & & \\ & & & & 0 & 1-q \\ & & & & & \ddots \\ q & & & & & & 1-q \end{bmatrix} \quad (4.45)$$

Let $\boldsymbol{\pi}$ be the steady state solution of the system, $\boldsymbol{\pi}\mathcal{P}_s = \boldsymbol{\pi}$. Then, the fraction of time slots in which a user issues updates is π_1

$$\pi_1 = \left(s + \frac{1-q}{q} \right)^{-1}. \quad (4.46)$$

Proof. From §4.6.3,

$$\pi_1 = \pi_i, \quad i = 1, \dots, s \quad (4.47)$$

$$\pi_i = \pi_{i-1}(1-q) = \pi_1(1-q)^{i-s}, \quad i = s+1, \dots, M-1 \quad (4.48)$$

$$\pi_M = (1-q)(\pi_{M-1} + \pi_M) = \frac{1-q}{q}\pi_{M-1} \quad (4.49)$$

Therefore,

$$\begin{aligned} \pi_1 &= \left(s + \sum_{i=s+1}^{M-1} (1-q)^{i-s} + (1-q)^{M-s}/q \right)^{-1} \\ &= \left(s + \sum_{i=1}^{M-1-s} (1-q)^i + (1-q)^{M-s}/q \right)^{-1} \\ &= \left(s + \frac{1-q}{q} \right)^{-1} \end{aligned} \quad (4.50)$$

□

Next, we derive a closed-form expression for the expected reward as a function of the threshold s . Replacing the expression of the steady state solution $\boldsymbol{\pi}$ into $E[r; s] = \sum_{i=1}^M \pi_i r(i, \mathbf{1}_{i \geq s})$ yields,

$$E[r; s] = \pi_1 \left[\sum_{x=1}^{s-1} U(x) + \sum_{i=0}^{M-1-s} U(i+s)(1-q)^i - \frac{G}{q} - P \right] \quad (4.51)$$

Proof. Let

$$\gamma = \left((U(M) - G - qP)\pi_M - \sum_{i=s}^{M-1} (G + qP)\pi_i \right) / \pi_1 \quad (4.52)$$

Then,

$$E[r; s] = \sum_{i=1}^{s-1} U(i)\pi_1 + \sum_{i=s}^M (U(i) - G - qP)\pi_i \quad (4.53)$$

$$\begin{aligned} &= \pi_1 \left[\sum_{i=1}^{s-1} U(i) + \sum_{i=s}^{M-1} U(i)\pi_i/\pi_1 + \gamma \right] \\ &= \pi_1 \left[\sum_{i=1}^{s-1} U(i) + \sum_{i=0}^{M-1-s} U(i+s)(1-q)^i \right. \\ &\quad \left. + \frac{1}{q}(1-q)^{M-s}(U(M)-G-qP) - (G+qP)\frac{1-(1-q)^{M-s}}{q} \right] \\ &= \pi_1 \left[\sum_{i=1}^{s-1} U(i) + \sum_{i=0}^{M-1-s} U(i+s)(1-q)^i - G/q - P \right] \end{aligned} \quad (4.54)$$

□

We use the expression above to show that the expected average reward is non-decreasing in s , for $s < s^*$, as stated in the following proposition.

Proposition 4.7. *The optimal threshold value s^* is*

$$s^* = \min \left\{ s \mid E[r; s] \geq E[r; s+1] \right\} \quad (4.55)$$

The proof of Proposition 4.7 follows directly from Proposition 4.8.

Proposition 4.8. *If $s \leq s^* - 1$ then $E[r; s] \leq E[r; s+1]$. Otherwise, $E[r; s] \geq E[r; s+1]$.*

Proof. Next, we show that if $s \leq s^* - 1$ then $E[r; s] \leq E[r; s+1]$ (the other case follows similarly). Let s^* be the optimal threshold. It follows from Definition 4.4 that $E[r; s] - E[r; s^*] \leq 0$ for $1 \leq s \leq M$. Next, we show that $E[r; s^* - m] \geq E[r; s^* - (m+1)]$ for $m < s^*$. The proof is by induction on m .

Algebraic manipulation of (4.51) yields

$$\begin{aligned} &\left(s-1 + \frac{1-q}{q} \right) E[r; s-1] - \left(s + \frac{1-q}{q} \right) E[r; s] \\ &= \left[\sum_{i=1}^{s-2} U(i) + \sum_{i=0}^{M-s} U(i+s-1)(1-q)^i - \frac{G}{q} - P \right] \end{aligned} \quad (4.56)$$

$$\begin{aligned} &- \left[\sum_{i=1}^{s-1} U(i) + \sum_{i=1}^{M-s} U(i+s-1)(1-q)^{i-1} - \frac{G}{q} - P \right] \\ &= -q \sum_{i=1}^{M-s} U(i+s-1)(1-q)^{i-1}. \end{aligned} \quad (4.57)$$

Equation (4.57) yields

$$\left(s + \frac{1-q}{q}\right) (E[r; s-1] - E[r; s]) = E[r; s] - q \sum_{i=1}^{M-s} U(i+s)(1-q)^{i-1} \quad (4.58)$$

Base case: It follows from Definition 4.4 that the statement holds for $m = 0$. Note that $E[r; s^* - 1] - E[r; s^*] \leq 0$ yields

$$\left(s^* - 1 + \frac{1-q}{q}\right) (E[r; s^* - 1] - E[r; s^*]) \quad (4.59)$$

$$\stackrel{(*)}{=} E[r; s^*] - q \sum_{i=1}^{M-s^*} U(i+s^*-1)(1-q)^{i-1} \quad (4.60)$$

$$= \left(s^* + \frac{1-q}{q}\right) (E[r; s^* - 1] - E[r; s^*]) \quad (4.61)$$

$$\stackrel{(**)}{=} E[r; s^* - 1] - q \sum_{i=1}^{M-s^*} U(i+s^*-1)(1-q)^{i-1} \leq 0$$

$$E[r; s^* - 1] \leq q \sum_{i=1}^{M-s^*} U(i+s^*-1)(1-q)^{i-1} \quad (4.62)$$

where (*) follows from (4.51) and (**) follows from (*) after summing $E[r; s^* - 1] - E[r; s^*]$ to both sides.

Induction hypothesis: Assume that $E[r; s^* - m] \geq E[r; s^* - (m+1)]$ for $m < t$.

Induction step: We show that the proposition holds for $m = t$. To this goal, we compare $E[r; s^* - t]$ and $E[r; s^* - (t+1)]$,

$$\begin{aligned} & \left(s^* - t + \frac{1-q}{q}\right) (E[r; s^* - t] - E[r; s^* - t - 1]) \\ \stackrel{(*)}{=} & q \sum_{i=1}^{M-s^*+t} U(i+s^*-t-1)(1-q)^{i-1} - E[r; s^* - t] \\ > & q \sum_{i=1}^{M-s^*} U(i+s^*-t-1)(1-q)^{i-1} - E[r; s^* - t] \\ > & q \sum_{i=1}^{M-s^*} U(i+s^*)(1-q)^{i-1} - E[r; s^* - t] \\ \stackrel{(**)}{\geq} & q \sum_{i=1}^{M-s^*} U(i+s^*)(1-q)^{i-1} - E[r; s^* - 1] \stackrel{(***)}{\geq} 0 \end{aligned}$$

where (*) follows from (4.58), (**) follows from the induction hypothesis and (***) follows from (4.62). The proof is completed by noting that $s^* - t + \frac{1-q}{q} \geq 0$ hence $E[r; s^* - t] \geq E[r; s^* - t - 1]$. \square

Finally, Proposition 4.9 formalizes the monotonicity of s^* with respect to G observed in §4.5.

Proposition 4.9. *The optimal threshold s^* is non-decreasing with respect to G and P .*

Proof. In what follows we show that the optimal threshold increases with respect to G . The proof that the optimal threshold increases with respect to P is similar. From (4.54),

$$\frac{d}{dG}E[r; s] = -\frac{1}{qs + 1 - q} \quad (4.63)$$

Let $s_1 > s_0$. Then,

$$\lim_{\Delta G \rightarrow 0} \frac{E[r; s_1, G + \Delta G] - E[r; s_1, G]}{\Delta G} > \lim_{\Delta G \rightarrow 0} \frac{E[r; s_0, G + \Delta G] - E[r; s_0, G]}{\Delta G} \quad (4.64)$$

From (4.54), it also follows that

$$E[r; s, G + \Delta G] - E[r; s, G] = -\frac{1}{s + (1 - q)/q} \frac{\Delta G}{q} \quad (4.65)$$

Therefore,

$$E[r; s_1, G] - E[r; s_1, G + \Delta G] < E[r; s_0, G] - E[r; s_0, G + \Delta G] \quad (4.66)$$

Assume, for the sake of contradiction, that s_1 and s_0 are optimal thresholds when the energy cost is G and $G + \Delta$, respectively,

$$E[r; s_1, G] \geq E[r; s, G], \quad s \neq s_1 \quad (4.67)$$

$$E[r; s_0, G + \Delta G] \leq E[r; s, G + \Delta G], \quad s \neq s_0 \quad (4.68)$$

In particular,

$$E[r; s_1, G] \geq E[r; s_0, G] \quad (4.69)$$

$$E[r; s_0, G + \Delta G] \leq E[r; s_1, G + \Delta G] \quad (4.70)$$

Then, $E[r; s_1, G] - E[r; s_1, G + \Delta G] \geq E[r; s_0, G] - E[r; s_0, G + \Delta G]$, which contradicts the (4.66). \square

4.7 Game Framework

In this section we consider strategic providers that offer *bonus* to users so as to control the WiFi network load and avoid congestion. Providers supporting multiple services in parallel, each service with its associated class and quality of service, may use the bonus to split resources among users in different classes. When the request rate in a given class increases, the provider might decrease the bonus to users of such a class to avoid congestion.

As in the single user scenario, the objective of each mobile user is to maximize his expected average reward. Users decide unilaterally to activate or not their mobile devices and to use WiFi if available. However, the choices of a user may now affect the outcome perceived by others, as the rewards of the users are coupled together. The rewards depend on the bonus set by providers, and if a user decides to activate his device, this might decrease the bonus offered by the provider to other users, which might in turn impact other users actions.

Let N be the population size, assumed to be constant, and let n_t be the number of active users that encounter an access point at time t . Let $B(n_t)$ be the bonus set by the provider, as a function of the number of active users n_t . In what follows, we assume that $B(n_t)$ is a decreasing function of n_t . To simplify presentation, in this section we assume users have access only to WiFi network. Therefore, the action of user i at time t , $a_{i,t}$, is zero (resp., one) when the user is inactive (resp., active), and $n_t = \sum_{i=1}^N a_{i,t}$. Henceforth, we omit subscript t when the time can be directly inferred from context.

At each time slot t , mobile user i receives an immediate reward of $r_i(x_i, a_i, a_{-i})$ as a result of choosing action a_i when the age of its message is x_i and the action selected by other users is given by $\mathbf{a}_{-i} = (a_1, \dots, a_{i-1}, a_{i+1}, \dots, a_N)$. The reward of user i at time t is obtained from (4.4) after accounting for the bonus, and is given by

$$r_i(x_i, a_i, a_{-i}) = \begin{cases} U(x_i), & \text{if } a_i = 0; \\ U(x_i) - G, & \text{if } a_i = 1 \text{ and } e = 0; \\ U(x_i) - G - P + B(n), & \text{if } a_i = 1 \text{ and } e = 1. \end{cases} \quad (4.71)$$

Note that we assume that users experience the same opportunities to access the WiFi network, *i.e.*, e does not depend on the user. This corresponds, for instance, to passengers inside the same bus or a cluster of people that move together with an intermittent access point in a military environment. The objective of user i consists of finding the strategy μ_i that maximizes its expected average reward, accounting for the impact of other users on the expected reward, *i.e.*, users act strategically, and aim at solving the following problem.

STRATEGIC USER PROBLEM: Obtain strategy μ so as to maximize $E[r; \mu]$, where

$$R_i(\mu_i, \mu_{-i}) = \lim_{\ell \rightarrow \infty} \frac{1}{\ell} \mathbb{E}_\mu \left[\sum_{t=1}^{\ell} r_i(x_{i;t}, a_{i;t}, a_{-i;t}) \right], \quad (4.72)$$

STRATEGIC USER PROBLEM presented above is within the scope of a class of stochastic games characterized by the following properties: (i) the state transition probabilities of a mobile user depend only on the actions of that user; (ii) each mobile user has information only about his own state and previous actions. It does not know the state and actions of other mobile users, and (iii) the reward function of a mobile user depends on the states and actions of all mobile users. Mobile users *interact, i.e., are coupled* only through the cost function.

4.8 Nash equilibrium

In this section we characterize the optimal response of individual mobiles and the threshold type Nash equilibrium strategy. We begin by describing the way an optimal mixed strategy response for mobile user i is computed for a given multi-strategy μ .

4.8.1 Best response function

We now derive the Best Response BR_i function of mobile user i . Let $p_i(\mu)$ be the steady state probability that user i is active given the multi-strategy μ ,

$$p_i(\mu) = \mu_i(1) = \sum_{x_i=1}^M \mu_i(1|x_i) \pi_i(x_i; \mu_i). \quad (4.73)$$

where $\pi_i(x_i; \mu_i)$ is the steady state (invariant) probability of the Markov chain describing the age process of mobile user i when the policy μ_i is used. The multi-strategy μ is fully characterized by $\mathbf{p} = (p_1, \dots, p_N)$ and the vector of strategies of all users other than i is denoted by $\mathbf{p}_{-i} = (p_1, \dots, p_{i-1}, p_{i+1}, \dots, p_N)$.

In what follows, we will consider the symmetric scenario where $p_1 = p_2 = \dots = p_{i-1} = p_{i+1} = \dots = p_N$. Let $p_{\neq i}$ be the probability that mobile user j is active, $j \neq i$. Let $\bar{B}(\mathbf{p}_{-i})$ be the average bonus received by user i when he is active,

$$\bar{B}(\mathbf{p}_{-i}) = \sum_{n=0}^{N-1} \binom{N-1}{n} p_{\neq i}^n (1 - p_{\neq i})^{N-n-1} B(n+1) \quad (4.74)$$

Let $r_i(x_i, a_i, \mu_{-i})$ denote the immediate reward induced by mobile users other than i , when mobile user i uses action a_i and the other users use a multi-strategy μ_{-i} . $r_i(x_i, a_i, \mu_{-i})$ is given by (4.71), substituting $B(n)$ by (4.74).

Definition 1. A mixed threshold policy corresponds to a strategy μ_i such that

$$\mu_i(x) = \begin{cases} 0, & \text{if } x < s_i \\ \theta_i, & \text{if } x = s_i \\ 1, & \text{if } x > s_i \end{cases} \quad (4.75)$$

If user i adopts a mixed threshold strategy, the probability that mobile user i is active, at steady state, is given by

$$p_i(\mu_i) = \pi_i(1; \mu_i) = \left(s_i + \frac{1 - \theta_i q}{q} \right)^{-1} \quad (4.76)$$

When user i adopts the mixed strategy μ_i , the average expected reward is given as a function of p_i and \mathbf{p}_{-i} as follows

$$\begin{aligned} R_i(p_i, \mathbf{p}_{-i}) &= \pi_i(1; \mu_i) \left[\sum_{x=1}^{s_i-1} U(x) - G/q - P + \bar{\mathbf{B}}(\mathbf{p}_{-i}) \right. \\ &\quad \left. + \sum_{x=0}^{M-1-s_i} U(x + s_i)(1 - q)^x \right] \end{aligned} \quad (4.77)$$

Definition 2. The best response function of mobile user i is

$$BR_i(\mathbf{p}_{-i}) = \operatorname{argmax}_{s_i} R_i(p_i, \mathbf{p}_{-i}), \quad i = 1, \dots, N \quad (4.78)$$

Let s_i^* be the optimal threshold for mobile user i when the other mobile users use \mathbf{p}_{-i} . As the threshold s_i^* yields a corresponding activation probability p_i^* , in what follows we refer to the best response of user i in terms of optimal thresholds or optimal activation probabilities interchangeably. The following theorem relies on dynamic programming to compute the best response for player i against a stationary policy μ_{-i} .

Proposition 4.10. *If the optimal threshold strategy is unique, the best response of mobile user i is*

$$BR(\mathbf{p}_{-i}) = \left\{ \left(s_i^* + \frac{1 - q}{q} \right)^{-1} \right\} \quad (4.79)$$

Otherwise,

$$BR(\mathbf{p}_{-i}) = \left[\left(s_i^* + \frac{1}{q} \right)^{-1}, \left(s_i^* + \frac{1 - q}{q} \right)^{-1} \right] \quad (4.80)$$

As $U(x)$ is non-increasing, one can show that there are at most two optimal thresholds. If the optimal threshold is unique, the best response is given by (4.76). Otherwise, if there are two optimal thresholds s_i^* and $s_i^* + 1$, randomizing between the two also yields an optimal policy. Therefore, if we allowed for randomized strategies, the best response of mobile user i would consist of choosing any activation probability in the interval $[(s_i^* + \frac{1}{q})^{-1}, (s_i^* + \frac{1-q}{q})^{-1}]$.

4.8.2 Symmetric Nash equilibrium

A symmetric Nash equilibrium \mathbf{p}^* is a set of strategies $\mathbf{p}^* = (p, p, \dots, p)$ such that

$$R_i(\mathbf{p}^*) \geq R_i(p_i, \mathbf{p}_{-i}^*), \quad i = 1, \dots, N \quad (4.81)$$

A policy $\mathbf{p}^* = (p, p, \dots, p)$ is a symmetric NE if, for every user i , $i = 1, \dots, N$, p belongs to the set of best response strategies of user i , when all other users adopt the stationary strategy p , *i.e.*, p is a symmetric NE if

$$p \in BR(\mathbf{p}_{-i}^*) \quad (4.82)$$

Lemma 4.11. *There exists an unique fixed point of (4.82)*

Proof. Similar to Proposition 4.9, we can show that the optimal threshold is non-increasing with respect to the bonus. The bonus $\bar{B}(\mathbf{p}_{-i})$, in turn, increases as the update probability p_{-i} of the other mobile users increases. This implies that the best response of user i is non-increasing with respect p_{-i} . Therefore, the higher the threshold adopted by other users, the lower is the optimal threshold for a given mobile user, and (4.82) admits a single fixed point, which may correspond to a pure strategy or a mixed strategy. \square

Proposition 4.12. *Let $\mathbf{p}^* = (p^*, \dots, p^*)$ be the symmetric fixed point of (4.82) with $p_s \leq p^* < p_{s+1}$. The stochastic game has a unique mixed symmetric Nash equilibrium μ^* which is given by*

$$\mu_j^*(x) = \begin{cases} 0, & \text{if } x < s \\ s + (1/q) - (1/p^*), & \text{if } x = s \\ 1, & \text{if } x > s \end{cases} \quad (4.83)$$

Figure 4.6(a) illustrates two best response functions (dotted and solid lines). The dotted line yields an equilibrium with pure strategies, marked with p_1^* , whereas the solid line yields an equilibrium with a mixed strategies, p_2^* .

After characterizing the equilibrium and its properties, we perform sensitivity analysis to understand how different parameters affect the equilibrium. In Figure 4.6(b) we plot the updating probability p at the equilibrium as a function of the availability of the AP, q , for different values of the maximal age M . The higher is the availability of the AP, the higher the frequency at which users request for updates. As M increases, in turn, users become less aggressive. Note that p^* never exceeds q . In Figure 4.6(c) we show how the population size N affects the equilibrium. As the population size increases, the activation probability in the equilibrium decreases. When the energy cost G incurred to maintain the mobile device active increases, users also tend to decrease the activation probability. For instance, note that for $N = 10$, p^* decreases by nearly 40% when the energy cost increases from 0.4 to 0.8.

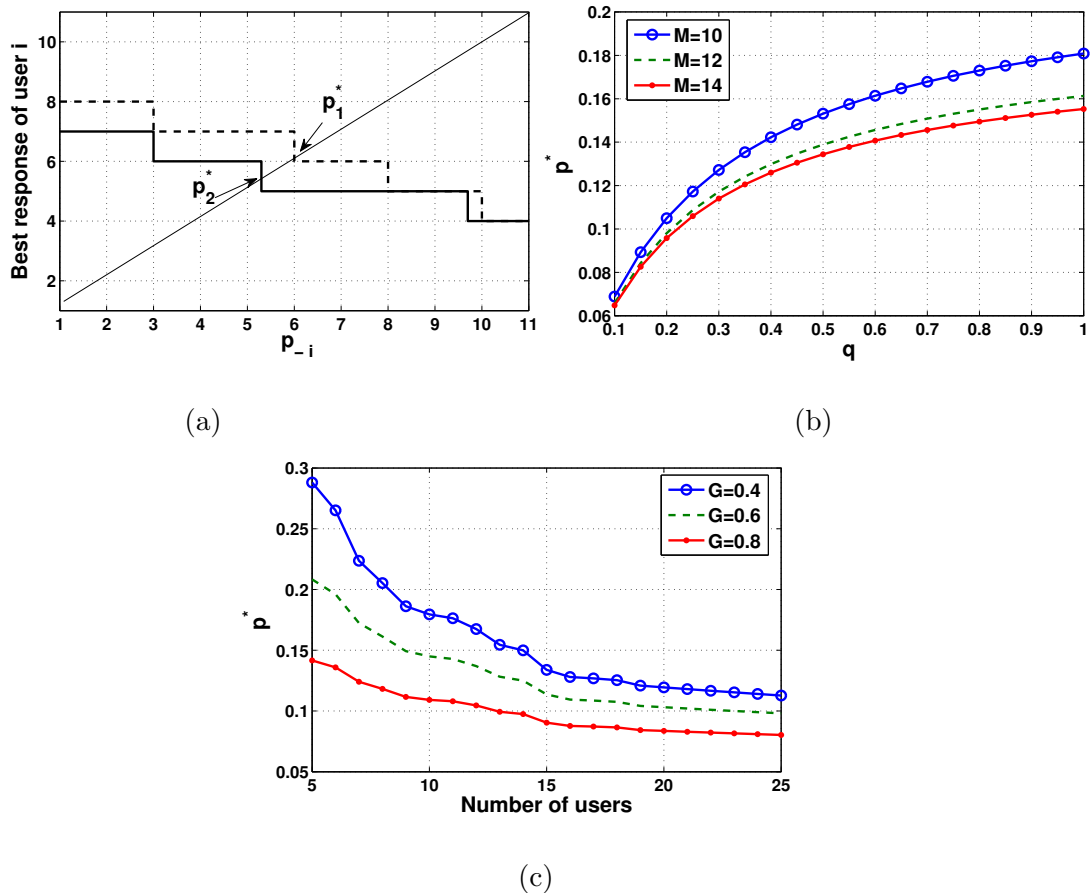


FIGURE 4.6: (a) Pure and mixed symmetric NE; (b) Impact of q on the equilibrium; (c) The equilibrium as a function of number of users

4.9 Assumptions and Limitations

Next, we discuss the main simplifications adopted to yield a tractable model.

Frequent decisions assumption: We assume that users are interested in maximizing their expected average rewards. This assumption is appropriate if decisions are made frequently. In our measurement study, we assumed that users make decisions every 5 minutes, and we observed that for a vast number of bus shifts the system parameters are stable over hours.

High load assumption: We assume that updates are issued every time slot with high probability. This assumption holds for certain news feeds categories such as *top stories*. The high load assumption also holds if users synchronize the updates of multiple applications, using APIs. In this case, the larger the number of applications that require updates, the higher the chances of at least one update being available every time slot. If multiple application updates can be performed at a single time slot, the bundle being subject to no additional costs or bonus, our model holds without modifications. However, if the interaction among the applications is non trivial, new policies need to be devised accounting for decisions such as when and from whom to download updates from each of the applications.

Self-regarding users assumption: We assume that users do not collaborate with each other. Although researchers are interested in leveraging collaboration among users [57, 64], a large number of mobile systems still does not take advantage of peer-to-peer transfers, and users need to download their messages exclusively from access points or base stations [55]. Our model applies to such systems. Nevertheless, we envision that if peers are roughly uniformly distributed, peer-assisted opportunistic transfers can be easily captured by our model simply by adapting the contact probability, q , in order to account for peer-to-peer contacts. Future work consists of accounting for spatial information when modeling the likelihood of contact opportunities.

4.10 Conclusion

In this chapter we report our measurement and modeling studies of aging control in hybrid wireless networks. From the DieselNet measurements, we learned that correlations among contact opportunities do not play a key role if the energy costs incurred by users are small or if users cannot discriminate their strategies based on bus shifts. We then modeled and solved the aging control problem, and used trace-driven simulations to show that a very simple threshold strategy derived from our model performs pretty well in practice. Moreover, we extend our analysis to multiple users competing for a bonus offered by publishers. We show the existence and the uniqueness of a mixed threshold policy. We believe that the study of mechanisms to support applications that require frequent updates, such as microblogging, in wireless networks, is an interesting field of

research, and we see this work as a first attempt to shed light into the tradeoffs faced by users and publishers of such applications.

Chapter 5

Optimal sensing policies in delay tolerant networks: A POMDP Approach

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5.1 Introduction

The ubiquity of mobile devices is fostering a paradigm shift in the realm of Internet services. Facebook alone counts with up to 800 million users, 41% of whom frequently access the social network through smartphones, and more than 475 mobile operators globally work to deploy and promote Facebook mobile products. Despite the fact that users are free to create accounts and upload content at sites like Facebook, they are faced with tradeoffs while deciding when and how to access the network from mobile devices.

As the population of users connected to social networks and sites alike keeps growing, status updates and notifications are generated at increasingly higher rates. As the time

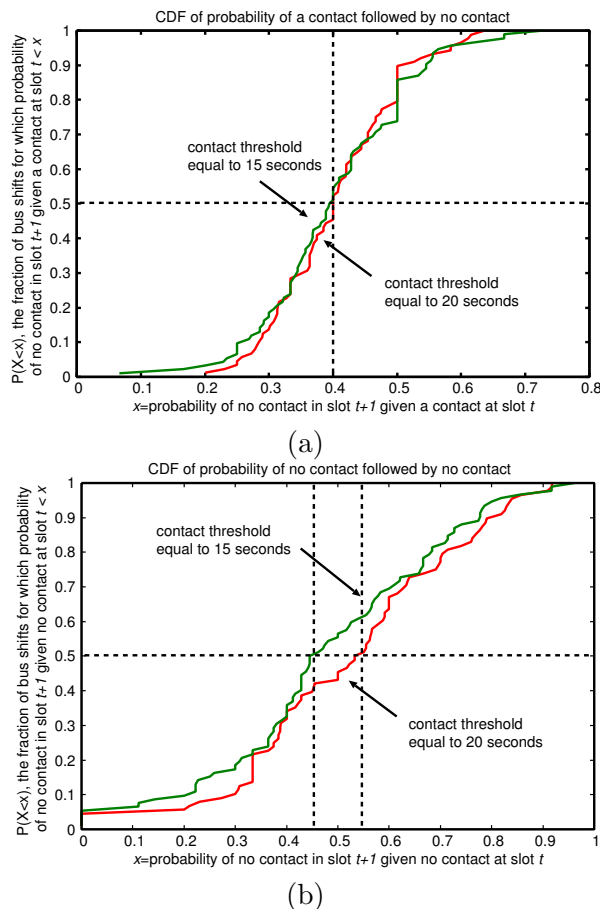


FIGURE 5.1: Contact opportunity CDF, (a) probability of a contact followed by no contact and (b) probability of no contact followed by no contact.

between updates decreases, users are faced with novel challenges. Mobile users accessing the network from mobile devices consume energy from limited batteries and their access might be subject to fees. We consider users that can access Internet either through a WiFi or 3G network. While the 3G network provides broader coverage [75], its usage requires a subscription to an operator and its monetary and energy costs are significantly higher than WiFi.

Let the *age* of a content¹ be the duration of time since the content was updated (*i.e.*, received) for the last time by a user. If a user is in the range of a service provider (WiFi access point or 3G antenna) and activates his mobile device, an update is received and the age of the message is reset to one, at the expense of a monetary and energy costs. Thus, users face a tradeoff between the costs and their *message utilities*. To cope with such a tradeoff, users decide, based on the availability of an access point and the age of the message, whether to activate the mobile device or not, and which technology to use (WiFi or 3G).

¹In this chapter, the terms content and message are used interchangeably.

There is a vast literature on sensing policies in the realm of cognitive radio networks [76–78]. Nonetheless, to the best of our knowledge none of the previous works considered the aging control problem under an incomplete information framework.

Focusing on cognitive radio networks, Zhao *et al.* [76] studied decentralized MAC protocols, where secondary users search for spectrum opportunities without a central controller. They propose an analytical framework based on a POMDP, and look for optimal sensing and channel selection schemes that maximize the expected total number of bits delivered over a finite number of slots. Optimal policies were derived depending on the history of decisions and observations of primary channels occupancy. Liu *et al.* [77] consider the interaction between secondary users who are trying to maximize their throughput. They also propose a POMDP in order to find an optimal opportunistic spectrum access policy.

Taking into account energy constraints in defining the optimal sensing policies is required to satisfy some QoS requirements. Few works have included the energy consumption in their policies definitions. Chen *et al.* [79] formulated the problem as a POMDP with a finite randomized horizon and Wang *et al.* [80] proposed an adaptive algorithm to find the optimal contention probability that minimizes the expected delay, in the context of a queueing analysis of a cognitive radio network with multiple secondary users. In a queueing context too, Altman *et al.* [81] propose a model based on MDP, where each user chooses dynamically both the power and the admission control to be adopted so as to maximize its expected throughput. The authors then studied the equilibria for the multi-player scenario in a stochastic game context.

Previous work that accounted for the aging control considered the problem from the perspective of providers or publishers [56, 61, 63]. In this work, we consider the problem from the perspective of users. In [56], using a spatial mean field approach, the authors model the distribution of message ages in a mobile network. Activation of mobile devices strategies were proposed in [82, 83]. In [83], the authors propose a joint activation and link selection control policy to minimize the energy consumption under delay constraints.

In the previous chapter, we consider a Markov Decision Process (MDP) model to derive the structure of the optimal aging control policy. However, we assumed that the probability to find a useful contact opportunity between a user and a WiFi access point is constant and independent across time slots. Since the correlations between contact opportunities experienced by a user are always present in real mobile network, in this chapter, we improve our model and overcome this limitation by using a POMDP rather than a MDP.

The main objective of this chapter is to derive the optimal activation and access policy for a mobile user. We refer to a policy which determines activation decisions as a function of message ages and the availability of access points as a *sensing policy*.

Given the scenario outlined above, we pose the following question: what is the users optimal sensing policy? In answering this question, we make the following contributions.

Model formulation: we propose an analytical model to capture the tradeoff faced by mobile users while receiving their content updates. Our model is based on the framework of partially observed Markov decision processes (POMDP), wherein the state of a user comprises the age of its message as well as the belief about the probability of meeting an access point in the upcoming time slot.

Optimal policy: using the proposed model, we show several Proposition satisfied by optimal policies. In particular, we show that there exists a threshold λ^* such that if the user's belief about the opportunity of contacting an AP is smaller than λ^* , it is optimal to remain idle. We establish monotonicity Proposition of the POMDP value function [74], and use them to get a closed-form expression for the threshold λ^* as a function of the system parameters. We also determine conditions on the age of the messages under which it is beneficial to access the network through WiFi as opposed to relying on the more costly 3G. The optimal policy can be determined using value iteration, and is simple enough to be easily implemented in off-the-shelf smartphones.

The organization of the remainder of this chapter is as follows. In the next section we describe the mobile user model. Section 5.3 formalizes the problem statement and Section 5.4 presents the partially observed Markov decision process framework. In Section 5.5 we use the proposed model to establish the structural Proposition of an optimal policy. Section 5.6 presents some numeric illustrations, in Section 5.7 we summarizes our observation and concludes the chapter.

5.2 Mobile User Model

The goal of a sensing policy is to control the aging of the messages so as to reduce energy and monetary costs. Whereas the energy reduction is clearly of interest to users, monetary cost reduction impacts both users and providers.

Due to the aforementioned reasons, open WiFi access points are becoming increasingly popular. Open WiFi access points motivate the sensing policies described in this chapter, as users encounter such access points in an ad hoc fashion. Alternatively, users can also use proprietary WiFi access point infrastructure installed by service providers. In both

cases, random factors such as fading and user speed determine the availability of the WiFi access points, which will vary in time and space.

5.2.1 Partially Observed Markov Decision Processes

We propose a general model that allows us to study the impact of energy costs, prices, utility of messages and their age on the sensing policy. Our problem is formulated as a partially observable Markov decision process (POMDP) [84],[85],[86]. *The POMDP accounts for the fact that contacts between WiFi access points and users occur in an unpredictable way (for the reasons pointed out above), but not uniformly at random (as illustrated in Section 5.2.2).* Our model allows us to naturally consider the effect of the actions at a given time slot on the future states of the system, and allows us to derive the structure of the optimal sensing policy.

5.2.2 Access Point Contacts Are Unpredictable But Correlated

In this section we use traces collected from the UMass Amherst DieselNet [87] to study the distribution of contact opportunities between mobile users and access points. Mobile users considered here are passengers and drivers of buses. To characterize the update opportunities experienced by users, we analyze contacts between buses and access points at the UMass campus. Each bus scans for connection with APs on the road, and when found, connects to the AP and records the duration of the connection [87]. We assume that when the mobile devices are active, scans for access points occur every σ seconds. The scan is terminated once an access point is found. It was empirically determined that a scanning frequency of $1/20$ seconds yields a good balance between efficiency and low energy expenditure [83], so we considered $\sigma = 15$ and $\sigma = 20$ in our study. An access point is considered useful once it is scanned in two consecutive intervals of σ seconds. Henceforth, we refer to contact opportunities that last at least σ seconds simply as *contacts*.

Figure 5.1(a) (resp., Figure 5.1(b)) shows the CDF of the probability of a contact followed by no contact (resp., no contact followed by no contact). Each bus shift is divided into time slots of five minutes. If there is a contact in a given slot, we mark the slot as a useful slot. For each bus shift we generate a string of zeros and ones, corresponding to useful and non-useful slots, respectively. Then, we compute, for each bus shift, the fraction of ones followed by zeros (Figure 5.1(a)) and the fraction of zeros followed by zeros (Figure 5.1(b)). A point (x, y) in Figure 5.1(a) (resp., Figure 5.1(b)) represents the fact that at a fraction y of the bus shifts the probability of no contact at slot $t + 1$ given a contact (resp., no contact) at slot t was smaller than x .

Figure 5.1(a) indicates that the median of the probability of a contact being followed by no contact is roughly 0.5, for $\sigma = 15$ and $\sigma = 20$. The probability is well approximated by a uniform distribution, in the range of $[0.2, 0.6]$. Figure 5.1(b), in contrast, shows that the median of the probability of no contact being followed by no contact is roughly 0.45 and 0.55 for $\sigma = 15$ and $\sigma = 20$, respectively. This indicates that even though access point contacts are unpredictable, there is correlation among them, which we capture in the formulation presented in Section 5.3 and the corresponding POMDP model introduced in Section 5.4.

5.3 Problem Statement

We consider a time slotted hybrid wireless network where mobile users receive update messages from a service provider using either WiFi access points or 3G antennas. The availability of an access point is determined by some random factors like attenuation (fading) and user speed. The availability of an access point is modeled by a time homogeneous discrete Markov process $\{s(t) : t \geq 0\}$, $s(t) \in \{0, 1\}$, where $s(t) = 1$ means that an access point is available and $s(t) = 0$ means that no access point is available at time t . The transition probabilities of the access point are denoted by $P(s'|s) = P(s(t) = s' | s(t-1) = s)$. Let β (resp., α) be the probability that no contact (resp., a contact) is followed by a contact. Let P be the access point availability transition matrix,

$$P = \begin{pmatrix} 1 - \beta & \beta \\ 1 - \alpha & \alpha \end{pmatrix}$$

The transition probabilities can be determined based on the statistics of the service provider, as illustrated in Section 5.2.2. We assume that the transition matrix P is known by mobile users. In practical scenarios, learning methods such as rate estimators and transition matrix estimators [88] allow mobile users to estimate the transition probabilities. Let $\pi(1)$ be the steady state probability of a contact,

$$\pi(1) = \frac{\beta}{1 - \alpha + \beta}. \quad (5.1)$$

A mobile user subscribes to receive content updates from publishers. This content is transmitted to users through messages sent by the service provider. The age of a message is defined as the duration of time (in time slots) since the message was updated the last time. The objective of a user is to minimize the age of its message taking into account its utility and energy and monetary costs. At each time slot the user has to choose between 1) being inactive during the slot 2) sensing and using an access point

if available, otherwise waiting for the rest of the slot or 3) sensing and using an access point if available, otherwise using 3G.

Note that the system state at time t is unknown to the user if he decides not to sense the channel at that time, *i.e.*, $s(t)$ is not fully observable. Let $\lambda(t)$ be the probability that the user has a useful contact opportunity with the access point at the beginning of slot t , given the mobile decision at time $t-1$ and its observation history. $\lambda(t)$ is also referred to as the *belief* of the user about the availability of access points at time t , immediately before the transition from $s(t-1)$ to $s(t)$.

Users decisions are based on two pieces of information: 1) the partial information about the access point state and 2) complete information about the age of the message it owns, which naturally yields a partially observable Markov decision process (POMDP). Assuming that users have complete information about the age of the message that they own corresponds to considering a system at which new updates are available with high probability at every time slot (therefore, the message aging process is deterministic given that users remain inactive). Alternatively, we could easily adapt our model to account for the light load regime, wherein messages do not necessarily age at every time slot even if users remain inactive. In the latter case, users would have incomplete information about the availability of access points as well as about their message ages. Nonetheless, to simplify notation, in the rest of this chapter we assume complete knowledge about age information.

Let x_t be the age of the message owned by a user at time t . Let $\lambda(t)$ be belief of the user about the availability of an access point at time t , immediately before the transition from $s(t-1)$ to $s(t)$. At each time slot t , the user chooses its action $a(t)$,

$$a(t) = \begin{cases} 0, & \text{wait for the next slot;} \\ 1, & \text{sense and use WiFi if available;} \\ 2, & \text{sense and use WiFi if available, otherwise 3G.} \end{cases}$$

We assume that actions are determined at the beginning of each time slot. When the mobile user decides to sense (*i.e.* $a(t) \neq 0$), he observes the availability of access points. We denote by $\theta(t)$ the observation outcome, where $\theta(t) = 1$ if an access point is available, and $\theta(t) = 0$ otherwise. The age of the message of interest increases by one if the user chooses to stay inactive or if he is not in range of an access point, and is reset to one otherwise. Let M be the maximum age of a message. Then,

$$x_{t+1} = \begin{cases} \min(x_t + 1, M), & \text{if } a(t) = 0 \text{ or } [a(t) = 1 \text{ and } \theta(t) = 0]; \\ 1, & \text{if } a(t) = 2 \text{ or } [a(t) = 1 \text{ and } \theta(t) = 1]. \end{cases}$$

At time slot t , the mobile user receives an instantaneous reward $r_t((\lambda, x), a)$ as a result of choosing action a when the system is in the state (λ, x) . The instantaneous reward is comprised of two components. A positive component represents the utility of the message the user is willing to update, $U(x_t)$. We assume that $U(x)$ is in general a non-increasing function of x , and consider a linear utility defined by $U(x) = M - x$ when deriving closed form expressions. The second component of the instantaneous reward is negative, and corresponds to the consumed energy and the monetary cost for each message transmitted. Let E be the cost incurred to maintain the mobile device active, measured in monetary units. Then, the energy cost e_t is given by

$$e_t(a(t)) = \begin{cases} E, & \text{if } a(t) = 1 \text{ or } a(t) = 2; \\ 0, & \text{if } a(t) = 0. \end{cases}$$

In addition to the cost incurred to maintain the device active and to sense the channel, there is an energy cost incurred to transmit WiFi and 3G packets. Each message transmitted incurs costs C and C_{3G} when transmitted through WiFi and 3G, respectively. Messages might also be associated to monetary charges set by the service provider. The prices charged to use WiFi and 3G can be taken into account in C and C_{3G} , respectively. When a user receives a message update, he is subject to a cost m_t ,

$$m_t(a(t), \theta(t)) = \begin{cases} C, & \text{if } [a(t) = 1 \text{ or } a(t) = 2] \text{ and } \theta(t) = 1; \\ C_{3G}, & \text{if } a(t) = 2 \text{ and } \theta(t) = 0. \end{cases}$$

Monetary and energy costs incurred to transmit content through WiFi are usually lower than the ones to transmit through 3G. Therefore, we assume $C_{3G} > C$. The instantaneous user reward at time t , $r_t((\lambda, x), a)$, is

$$r_t((\lambda, x), a) = \begin{cases} U(x), & \text{if } a(t) = 0 ; \\ U(x) - E, & \text{if } a(t) = 1 \text{ and } \theta(t) = 0; \\ U(x) - E - C, & \text{if } [a(t) = 1 \text{ or } a(t) = 2] \text{ and } \theta(t) = 1; \\ U(x) - E - C_{3G}, & \text{if } a(t) = 2 \text{ and } \theta(t) = 0. \end{cases}$$

Assumption 2 (Active at maximum age). The user chooses to sense the channel if the age of the message reaches its maximum value.

Assumption 2 is a natural assumption, and corresponds to the fact that when $x_t = M$ the user has no incentive for idle waiting, and will choose between using WiFi if available (action 1) or using 3G otherwise (action 2).

5.4 Partially Observable Markov Decision Process Framework

We now describe the partially observable Markov decision process (POMDP) used to answer the problem formulated in the previous section. One of the key ingredients of the POMDP is the update rule for the belief state of the mobile at time t , $\lambda(t)$. The belief is updated at the end of each time slot based on the action $a(t)$ and the observation outcome $\theta(t)$.

Let $\Omega(\cdot|a(t), \theta(t))$ be the update rule operator on the belief value.² The update rule over the belief state about the availability of an access point is given by

$$\lambda(t+1) = \Omega(\lambda(t)|a(t), \theta(t)) \quad (5.2)$$

where

$$\Omega(\lambda(t)|a(t), \theta(t)) = \begin{cases} \alpha, & \text{if } [a(t) = 1 \text{ or } a(t) = 2] \text{ and } \theta(t) = 1; \\ \beta, & \text{if } [a(t) = 1 \text{ or } a(t) = 2] \text{ and } \theta(t) = 0; \\ \lambda(t)(\alpha - \beta) + \beta, & \text{if } a(t) = 0. \end{cases}$$

We suppose that a mobile user chooses arbitrarily an access point if he is in the range of more than one of them. The choice of an access point among the available ones is beyond the scope of this study, and can be made based on the throughput, the load or any other performance metric.

A sensing policy μ for our POMDP is given by a vector $[\mu_1, \mu_2, \dots]$, where each μ_t is a mapping from an information state $(\lambda(t), x_t)$ to an action $a(t)$ to be taken in slot t . We say that a policy is *stationary* if the function μ_t does not depend on time t , but only on the information state. A policy strikes a balance between instantaneous reward gains and information collection for future use. In this chapter we restrict to Markovian stationary policies, and in what follows we omit the time index t from all variables. It can be shown that the restriction to Markovian stationary policies can be made without loss of generality [74].

We look for an optimal policy that maps each system state (λ, x) to an action a . Our aim is to maximize the expected average reward. We denote the optimal policy by μ^* . The expected average reward is given by

$$R(r, \mu) = \lim_{T \rightarrow \infty} \frac{1}{T} \mathbb{E}_\mu \left[\sum_{t=1}^T r_t((\lambda, x), a, \theta) \middle| \lambda(1) \right], \quad (5.3)$$

² It has been proved in [76] that the belief $\lambda(t)$ together with the update rule operator $\Omega(\cdot|a(t), \theta(t))$ yield a sufficient statistic for the optimal action at time slot t .

where \mathbb{E}_μ represents the conditional expectation given that policy μ is employed and $\lambda(1)$ is the initial state belief, which can be an arbitrary distribution. The optimal policy μ^* is

$$\mu^* = \arg \max_{\mu} \left\{ R(r, \mu) \right\}. \quad (5.4)$$

Let \mathcal{P}_μ be the transition probability matrix of the Markov chain $\{(x_t, \lambda_t), t = 1, 2, \dots\}$ which characterizes the dynamics of the age and of the belief about contact opportunities, for a given policy μ . Let the POMDP *average reward per time slot in steady state*, when policy μ is adopted, be g_μ [74]. As the system transition matrix \mathcal{P}_μ comprises a single connected component, g_μ is constant and does not depend on the initial system state.

Let $V((\lambda, x), t; \mu)$ be the difference between the expected total reward accumulated by time t when the system starts in (λ, x) and the expected total reward accumulated when the system starts in steady state. Let $r_\mu(\lambda, x)$ be the expected instantaneous reward received in a time slot when the system is at state (λ, x) and policy μ is used; \mathbf{r}_μ is the vector of expected instantaneous rewards. Let $V((\lambda, x); \mu)$ be the *value function* at state (λ, x) , defined as a function of $V((\lambda, x), t; \mu)$ as

$$V((\lambda, x); \mu) = \left(\lim_{l \rightarrow \infty} V((\lambda, x), l; \mu) \right) (\lambda, x) \quad (5.5)$$

$$= \left(\lim_{l \rightarrow \infty} \sum_{t=0}^l \mathcal{P}_\mu^t (\mathbf{r}_\mu - g_\mu \mathbf{e}) \right) (\lambda, x) \quad (5.6)$$

where \mathbf{e} is a column vector with all its elements equal to one.

Let $Q_a(\lambda, x; \mu)$ be the relative expected average reward obtained by a user that takes action a when the belief value is λ and the age is x . Next, we provide expressions for the relative reward $Q_a(\lambda, x; \mu)$ as a function of the chosen action a .

Case 1 ($a = 0$): The user decides to turn off his mobile device, *i.e.*, $a = 0$, obtains an instantaneous reward of $U(x)$, the age of the message increases by one, and the belief is updated,

$$Q_0(\lambda, x) = U(x) + V(\Omega(\lambda|0), x + 1). \quad (5.7)$$

Case 2 ($a = 1$): The user decides to sense, consumes energy E and gets an observation θ . According to this observation, the user turns off his mobile device if $\theta = 0$ (in which case the age will increase), or uses WiFi if $\theta = 1$ (and the age is reset to one),

$$Q_1(\lambda, x) = U(x) - E + (1 - \lambda)V(\Omega(\lambda|1, 0), x + 1) + \lambda[-C + V(\Omega(\lambda|1, 1), 1)]. \quad (5.8)$$

Case 3 ($a = 2$): The user decides to sense, and uses 3G if WiFi is not available,

$$Q_2(\lambda, x) = U(x) - E + (1 - \lambda)[-C_{3G} + V(\Omega(\lambda|2, 0), 1)] + \lambda[-C + V(\Omega(\lambda|2, 1), 1)]. \quad (5.9)$$

Note that $\Omega(\lambda|1, 1) = \Omega(\lambda|2, 1) = \alpha$ and $\Omega(\lambda|1, 0) = \Omega(\lambda|2, 0) = \beta$. It follows from [74, eq. (8.4.2)] that a policy μ^* which satisfies the following conditions is optimal,

$$g_{\mu^*} + V(\lambda, x; \mu^*) = \max_a \{Q_a(\lambda, x; \mu^*)\}. \quad (5.10)$$

The optimal action at state (λ, x) is

$$a^*(\lambda, x) = \arg \max_a \{Q_a(\lambda, x; \mu^*)\}. \quad (5.11)$$

Henceforth, we also consider the following assumption.

Proposition 1. Assume that $\alpha \geq \beta$.

An extension to this work can be investigating the extent at which our results still hold if Assumption 1 is not satisfied.

5.5 Optimal Policy

In this section we present our key results concerning the structure of the optimal policy. After introducing monotonicity Proposition of the value function in Section 5.5.1, we establish Proposition about the optimal policy in Section 5.5.2.

5.5.1 Monotonicity of Value Function

A first step in establishing the structure of optimal policies is to study the monotonicity of the value function, which also provides insights into the problem under study [89].

Proposition 2. The value function $V(\lambda, x)$ is monotonically decreasing with the age of message x , for all belief λ ,

$$V(\lambda, x) > V(\lambda, x'), \text{ for } x < x', 0 \leq \lambda \leq 1 \quad (5.12)$$

Proof. According to Assumption 2, when the age reaches the maximum value $x = M$, the user chooses to sense ($a = 1$ or $a = 2$). We consider two cases,

Case 1) $Q_2(\lambda, M) > Q_1(\lambda, M)$

At age $x = M$, it follows from (5.10) that

$$\begin{aligned} g_\mu + V(\lambda, M) &= Q_2(\lambda, M) \\ &= U(M) - E + (1 - \lambda)(-C_{3G} + V(\beta, 1)) + \lambda(-C + V(\alpha, 1)) \end{aligned} \quad (5.13)$$

At age $x = M - 1$, it follows from (5.10) that

$$\begin{aligned} g_\mu + V(\lambda, M - 1) &= \max \left\{ Q_0(\lambda, M - 1); Q_1(\lambda, M - 1); Q_2(\lambda, M - 1) \right\} \\ &\geq Q_2(\lambda, M - 1) \end{aligned} \quad (5.14)$$

$$\begin{aligned} &= U(M - 1) - E + \\ &\quad (1 - \lambda)(-C_{3G} + V(\beta, 1)) + \lambda(-C + V(\alpha, 1)) \end{aligned} \quad (5.15)$$

$$\begin{aligned} &\geq U(M) - E + \\ &\quad (1 - \lambda)(-C_{3G} + V(\beta, 1)) + \lambda(-C + V(\alpha, 1)) \end{aligned} \quad (5.16)$$

$$= Q_2(\lambda, M) = g_\mu + V(\lambda, M) \quad (5.17)$$

Therefore, $V(\lambda, M - 1) \geq V(\lambda, M)$, and the result is proved for $x = M - 1$. To prove the result for $x < M - 1$, we use backward induction,

Initial condition: $V(\lambda, M - 1) \geq V(\lambda, M)$, $0 \leq \lambda \leq 1$

Induction hypothesis: Given x_0 , $1 < x_0 \leq M - 1$, we assume that $V(\lambda, x) \geq V(\lambda, x + 1)$, $x_0 \leq x \leq M - 1$, $0 \leq \lambda \leq 1$.

Induction step: Next, we show that if the result holds for x it holds for $x - 1$, $x > 1$,

$$\begin{aligned} V(\lambda, x - 1) &= \max \left\{ Q_0(\lambda, x - 1); Q_1(\lambda, x - 1); Q_2(\lambda, x - 1) \right\} \\ &= U(x - 1) + \max \left\{ V(\Omega(\lambda|0), x); \right. \end{aligned} \quad (5.18)$$

$$\begin{aligned} &\quad -E + (1 - \lambda)V(\beta, x) + \lambda(-C + V(\alpha, 1)); \\ &\quad \left. -E + (1 - \lambda)(-C_{3G} + V(\beta, 1)) + \lambda(-C + V(\alpha, 1)) \right\} \end{aligned}$$

$$\geq U(x) + \max \left\{ V(\Omega(\lambda|0), x + 1); \right. \quad (5.19)$$

$$\begin{aligned} &\quad -E + (1 - \lambda)V(\beta, x + 1) + \lambda(-C + V(\alpha, 1)); \\ &\quad \left. -E + (1 - \lambda)(-C_{3G} + V(\beta, 1)) + \lambda(-C + V(\alpha, 1)) \right\} \\ &\geq V(\lambda, x) \end{aligned}$$

where (5.19) follows from (5.18) due to the induction hypothesis.

Case 2) $Q_1(\lambda, M) \geq Q_2(\lambda, M)$

The proof for case 2) is similar to that for case 1).

□

Proposition 2 states that, for a given belief state, an updated message yields higher expected reward than an old message.

Lemma 1. We have the following property

$$\lambda \leq \pi(1) \Rightarrow \Omega(\lambda) \geq \lambda \quad (5.20)$$

Proof. As we assumed that $\alpha \geq \beta$, the update function $\Omega(\lambda)$ is increasing with respect to the belief λ . We now show by induction on time t that if $\lambda(t_0) \leq \pi(1)$ then $\Omega(\lambda(t)) \geq \lambda(t)$ for $t \geq t_0$.

We assume, without loss of generality, that $\lambda(t_0) = \beta$.

Initial condition: Note that $\beta \leq \pi(1)$ and $\Omega(\beta) = (\alpha - \beta)\beta + \beta \geq \beta$

Induction hypothesis: Assume that if $\lambda(t) \leq \pi(1)$ then $\Omega(\lambda(t)) \geq \lambda(t)$, $t_0 \leq t \leq t_1$.

Induction step: We want to show that if $\lambda(t+1) \leq \pi(1)$ then $\Omega(\lambda(t+1)) \geq \lambda(t+1)$,

$$\Omega(\lambda(t+1)) = \Omega(\Omega(\lambda(t))) \quad (5.21)$$

$$= (\alpha - \beta)\Omega(\lambda(t)) + \beta \quad (5.22)$$

$$\geq (\alpha - \beta)\lambda(t) + \beta \quad (5.23)$$

$$= \alpha\lambda(t) + \beta(1 - \lambda(t)) \quad (5.24)$$

$$\geq \lambda(t+1) \quad (5.25)$$

Where (5.23) follows from (5.22) by the induction hypothesis, and (5.25) follows from (5.24) due to (5.3). □

Proposition 3. The value function $V(\lambda, x)$ is monotonically increasing with the belief λ , for all ages x ,

$$V(\lambda, x) > V(\lambda', x), \text{ for } \lambda' < \lambda, x = 1, 2, \dots, M \quad (5.26)$$

Proof. According to Assumption 2, when the age reaches the maximum value $x = M$, the user chooses to sense ($a = 1$ or $a = 2$). We consider two cases,

Case 1) We assume that

$$Q_1(\lambda, M) \geq Q_2(\lambda, M) \quad (5.27)$$

In this case, we rely on the following lemma. The proof is provided in the next subsection.

Lemma 2.

$$-C + V(\alpha, 1) \geq V(\beta, M) \quad (5.28)$$

Given a real number λ' , $0 < \lambda' < 1$, for all $\lambda \leq \lambda'$ we have

$$\begin{aligned} V(\lambda, M) &= -g_\mu + U(M) - E + \\ &\quad (1 - \lambda)V(\beta, M) + \lambda(-C + V(\alpha, 1)) \end{aligned} \quad (5.29)$$

$$\begin{aligned} &= -g_\mu + U(M) - E + \\ &\quad V(\beta, M) + \lambda(-C + V(\alpha, 1) - V(\beta, M)) \end{aligned} \quad (5.30)$$

$$\begin{aligned} &\leq -g_\mu + U(M) - E + \\ &\quad V(\beta, M) + \lambda'(-C + V(\alpha, 1) - V(\beta, M)) \end{aligned} \quad (5.31)$$

$$= V(\lambda', M) \quad (5.32)$$

where (5.31) follows from (5.30) due to (5.28).

Using backward induction, we have

$$\textit{Initial condition: } V(\lambda, M) \leq V(\lambda', M), \quad 0 \leq \lambda \leq \lambda'$$

Induction hypothesis: Given x_0 , $1 < x_0 \leq M - 1$, we assume that $V(\lambda, x + 1) \leq V(\lambda', x + 1)$, $x_0 \leq x \leq M - 1$, $0 \leq \lambda \leq 1$.

Induction step: Next, we show that if the result holds for $x + 1$ it holds for x , $x \geq 1$.

Recall that $\pi(1)$ is the stationary probability that the access point is available. Then, $\Omega(\pi(1)) = \pi(1)$, and $\pi(1) = \beta/(1 - \alpha + \beta)$. We have shown in lemma 1 that

$$\lambda \leq \pi(1) \Rightarrow \Omega(\lambda) \geq \lambda$$

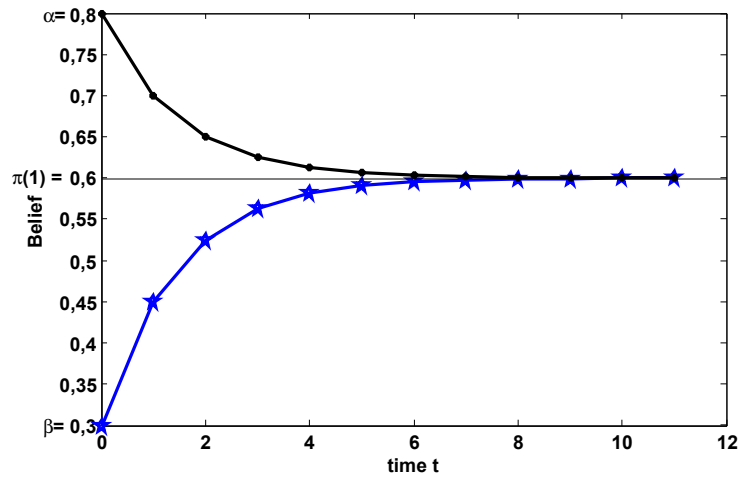
Figure 5.2 illustrates the evolution of the belief λ over time, obtained from (5.3), for $a = 0$, when $\alpha \geq \beta$ (see Assumption 1).

First, we show that $Q_0(\lambda, x) \leq Q_0(\lambda', x)$.

$$Q_0(\lambda, x) = U(x) + V(\Omega(\lambda|0), x + 1) \quad (5.33)$$

$$\leq U(x) + V(\Omega(\lambda'|0), x + 1) \quad (5.34)$$

$$= Q_0(\lambda', x)$$

FIGURE 5.2: Evolution of $\lambda(t)$ for $a = 0$ ($\alpha = 0.8$, $\beta = 0.3$).

Second, we show that $Q_2(\lambda, x) \leq Q_2(\lambda', x)$.

$$Q_2(\lambda, x) = U(x) - E + \lambda(-C + V(\alpha, 1)) \quad (5.35)$$

$$+ (1 - \lambda)(-C_{3G} + V(\beta, 1))$$

$$= U(x) - E - C_{3G} + V(\beta, 1) \quad (5.36)$$

$$+ \lambda(-C + V(\alpha, 1) + C_{3G} - V(\beta, 1))$$

As $Q_1(\lambda, M) \geq Q_2(\lambda, M)$ (see (5.27)), it follows that

$$V(\beta, M) > -C_{3G} + V(\beta, 1) \quad (5.37)$$

(5.37) together with (5.28) yields

$$-C + V(\alpha, 1) + C_{3G} - V(\beta, 1) > 0 \quad (5.38)$$

Replacing (5.38) into (5.36),

$$Q_2(\lambda, x) \leq U(x) - E - C_{3G} + V(\beta, 1)$$

$$+ \lambda'(-C + V(\alpha, 1) + C_{3G} - V(\beta, 1))$$

$$\leq Q_2(\lambda', x) \quad (5.39)$$

Third, we show that $Q_1(\lambda, x) \leq Q_1(\lambda', x)$.

If $-C + V(\alpha, 1) - V(\beta, x + 1) \geq 0$,

$$Q_1(\lambda, x) = U(x) - E + V(\beta, x + 1) \quad (5.40)$$

$$\begin{aligned} & + \lambda(-C + V(\alpha, 1) - V(\beta, x + 1)) \\ & \leq U(x) - E + V(\beta, x + 1) \end{aligned} \quad (5.41)$$

$$\begin{aligned} & + \lambda'(-C + V(\alpha, 1) - V(\beta, x + 1)) \\ & \leq Q_1(\lambda', x) \end{aligned} \quad (5.42)$$

If $-C + V(\alpha, 1) - V(\beta, x + 1) < 0$,

$$Q_1(\lambda, x) \leq U(x) - E + V(\beta, x + 1) \quad (5.43)$$

$$\leq U(x) - E + V(\Omega(\lambda|0), x + 1) \quad (5.44)$$

$$\leq Q_0(\lambda, x) \quad (5.45)$$

$Q_1(\lambda, x) \leq Q_0(\lambda, x)$ implies that the value function can either be equal to $Q_0(\lambda, x)$ or $Q_2(\lambda, x)$. Then

$$g_\mu + V(\lambda, x) = \max \{Q_0(\lambda, x), Q_2(\lambda, x)\}.$$

We have shown that $Q_0(\lambda, x)$, $Q_1(\lambda, x)$ and $Q_2(\lambda, x)$ are increasing with respect to the belief. Thus $V(\lambda, x) \leq V(\lambda', x)$ for $\lambda \leq \lambda'$ ($x = 0, 1, \dots, M$).

Case 2) We assume that $Q_2(\lambda, M) > Q_1(\lambda, M)$. In this case, we have the following lemma.

Lemma 3.

$$-C + V(\alpha, 1) \geq -C_{3G} + V(\beta, 1) \quad (5.46)$$

Using (5.46), the remainder of the proof for case 2) is similar to that for case 1). \square

According to Proposition 3, for a given age, the higher the belief that a contact will occur, the higher the expected reward.

Proof of Lemma 2:

We prove (5.28) by contradiction. Suppose that

$$-C + V(\alpha, 1) < V(\beta, M) \quad (5.47)$$

If $\lambda = \beta$ and $x = M$, it follows from (5.10) that

$$g_\mu = U(M) - E + \beta(-C + V(\alpha, 1) - V(\beta, M)) \quad (5.48)$$

If $\lambda = \alpha$ it follows from (5.10) that

$$g_\mu + V(\alpha, 1) = \max \{Q_1(\alpha, 1); Q_2(\alpha, 1)\} \quad (5.49)$$

$$\geq Q_2(\alpha, 1) \quad (5.50)$$

$$\geq U(1) - E + \alpha(-C + V(\alpha, 1)) \quad (5.51)$$

$$+ (1 - \alpha)(-C + V(\alpha, 1))$$

$$\geq U(1) - E - C + V(\alpha, 1) \quad (5.52)$$

$$g_\mu \geq U(1) - E - C \geq 0 \quad (5.53)$$

From (5.48) and (5.53) we have

$$\beta(-C + V(\alpha, 1) - V(\beta, M)) \geq U(1) - C \geq 0 \quad (5.54)$$

(5.54) is a contradiction with (5.47). Therefore, $-C + V(\alpha, 1) \geq V(\beta, M)$. ■

Proof of Lemma 3:

We prove (5.46) by contradiction. Suppose that

$$-C + V(\alpha, 1) < -C_{3G} + V(\beta, 1) \quad (5.55)$$

Then, it follows from (5.10) that

$$g_\mu + V(\alpha, 1) = \max \{Q_1(\alpha, 1); Q_2(\alpha, 1)\} \quad (5.56)$$

$$\geq Q_2(\alpha, 1)$$

$$\geq U(1) - E + \alpha(-C + V(\alpha, 1)) \quad (5.57)$$

$$+ (1 - \alpha)(-C + V(\alpha, 1))$$

$$\geq U(1) - E - C + V(\alpha, 1) \quad (5.58)$$

$$g_\mu \geq U(1) - E - C \geq 0 \quad (5.59)$$

Given the message age x , let us find the optimal action a .

At $x = M - 1$,

$$Q_0(\lambda, M - 1) \leq V(\lambda, M) + (\Omega(\lambda|0) - \lambda) \times (-C + V(\alpha, 1) + C_{3G} - V(\beta, 1)) \quad (5.60)$$

$$\leq V(\lambda, M) \leq V(\lambda, M - 1) \quad (5.61)$$

It follows from (5.61) and (5.59) that

$$Q_0(\lambda, M - 1) < V(\lambda, M - 1) + g_\mu \quad (5.62)$$

(5.62) together (5.10) imply that action 0 is not the optimal action at $M - 1$.

$$Q_1(\lambda, M - 1) - Q_2(\lambda, M - 1) = (1 - \lambda)(V(\beta, M) + C_{3G} - V(\beta, 1)) \quad (5.63)$$

$$\leq (1 - \lambda)(U(M) - E) \quad (5.64)$$

$$\leq -E(1 - \lambda) \leq 0 \quad (5.65)$$

It follows from (5.65) and (5.62) that action 2 is the optimal action at $M - 1$.

We proceed with backward induction.

Initial condition: Action 2 is the optimal action at $M - 1$.

Induction hypothesis: Given $x_0 > 0$, assume that action 2 is the optimal action at x , $x \geq x_0$.

Induction step: We now show that if action 2 is the optimal action at x , $x \geq x_0$, it is also the best action at $x - 1$.

From (5.7) we have

$$Q_0(\lambda, x - 1) \leq V(\lambda, x) + (\Omega(\lambda|0) - \lambda)(-C + V(\alpha, 1) + C_{3G} - V(\beta, 1)) \quad (5.66)$$

$$\leq V(\lambda, x) \leq V(\lambda, x - 1) \quad (5.67)$$

Thus, it follows from (5.67) that action 0 is not the optimal action at $x - 1$.

$$\begin{aligned} Q_1(\lambda, x - 1) &= U(x - 1) - E + \lambda(-C + V(\alpha, 1)) \\ &\quad + (1 - \lambda)V(\beta, x) \end{aligned} \quad (5.68)$$

$$\begin{aligned} &< U(x - 1) - E + \lambda(-C + V(\alpha, 1)) \\ &\quad + (1 - \lambda)(-C_{3G} + V(\beta, 1)) \end{aligned} \quad (5.69)$$

$$< Q_2(\lambda, x - 1) \quad (5.70)$$

It follows from (5.70) and (5.67) that action 2 is the optimal action at $x - 1$, given that it is optimal at x .

Action 2 is the optimal action for $\lambda \leq \pi(1)$ and $x \geq 0$. Considering the special case $\lambda = \beta$, (5.10) and (5.9) yield

$$\begin{aligned} V(\beta, 1) &= U(1) - E + \beta(-C + V(\alpha, 1)) \\ &\quad + (1 - \beta)(-C_{3G} + V(\beta, 1)) - g_\mu \end{aligned} \quad (5.71)$$

It follows from (5.59) and (5.71) that

$$\beta(-C + V(\alpha, 1) + C_{3G} - V(\beta, 1)) - C_{3G} \geq -C \quad (5.72)$$

Then, $C_{3G} \geq C$ together with (5.72) yields a contradiction with (5.55). Therefore, $-C + V(\alpha, 1) \geq -C_{3G} + V(\beta, 1)$. ■

5.5.2 Optimal Policy

In this subsection we derive the characteristics of an optimal policy for a mobile user. Intuitively, when the user belief λ about a future contact opportunity is large, and when the age of the message x is small, it is beneficial to remain inactive, and to wait and sense the channel at a future point in time. After sensing the channel, depending on the availability of an access point, the user will decide to get an update. The more outdated is the message, the more likely it is that the user will get updates using the 3G network. In what follows, we formalize the above intuition.

We start by deriving the optimal threshold for the scenario at which a user remains inactive, *i.e.*, when $a^*(\lambda, x) = 0$,

Proposition 4. For every information state (λ, x) , the user chooses to turn off his mobile device if $\lambda \leq \lambda^*$ where λ^* satisfies

$$\lambda^* = \max \left\{ \min \{ \rho_1(\lambda^*, x), \rho_2(\lambda^*, x) \}, 0 \right\}. \quad (5.73)$$

and

$$\rho_1(\lambda^*, x) = \frac{V(\Omega(\lambda^*|0), x+1) - V(\beta, x+1) + E}{-C + V(\alpha, 1) - V(\beta, x+1)} \quad (5.74)$$

$$\rho_2(\lambda^*, x) = \frac{V(\Omega(\lambda^*|0), x+1) - V(\beta, 1) + E + C_{3G}}{V(\alpha, 1) - V(\beta, 1) - C + C_{3G}} \quad (5.75)$$

Proof. Let us prove that a user will turn off his mobile device if the belief λ is lower than or equal to λ^* defined in the proposition. At each time slot, with a given information state (λ, x) , the user will decide to idle wait if the expected average reward of this action is larger than the one obtained through other actions.

Action $a(\lambda, x) = 0$ is at least as good as $a(\lambda, x) = 1$ iff

$$\begin{aligned} U(x) + V(\Omega(\lambda|0), x+1) &\geq \\ (1-\lambda)V(\beta, x+1) + \lambda(-C + V(\alpha, 1)) + U(x) - E &\quad (5.76) \end{aligned}$$

$$\begin{aligned} V(\Omega(\lambda|0), x+1) &\geq \\ -E + V(\beta, x+1) + \lambda(-C + V(\alpha, 1) - V(\beta, x+1)) &\quad (5.77) \end{aligned}$$

If $-C + V(\alpha, 1) - V(\beta, x+1) \neq 0$, (5.74) follows from (5.77), and action $a(\lambda, x) = 0$ is at least as good as $a(\lambda, x) = 1$ if (5.77) holds. If $-C + V(\alpha, 1) - V(\beta, x+1) = 0$, (5.77) together with Proposition 3 also imply that action 0 is at least as good as action 1. Action $a(\lambda, x) = 0$ is at least as good as $a(\lambda, x) = 2$ iff

$$\begin{aligned} U(x) + V(\Omega(\lambda|0), x+1) &\geq \\ (1-\lambda)(-C_{3G} + V(\beta, 1)) + \lambda(-C + V(\alpha, 1)) + U(x) - E & \\ V(\Omega(\lambda|0), x+1) &\geq -E + V(\beta, 1) \\ -C_{3G} + \lambda(-C + V(\alpha, 1) + C_{3G} - V(\beta, 1)) &\quad (5.78) \end{aligned}$$

As $V(\alpha, 1) > V(\beta, 1)$ and $C_{3G} > C$, we have that $V(\alpha, 1) - V(\beta, 1) - C + C_{3G} > 0$ and the definition of $\rho_2(\lambda, x)$ in (5.75) follows from (5.78).

□

Note that if $-C + V(\alpha, 1) - V(\beta, x+1) = 0$, we have $\lambda^* = \max(\rho_2(\lambda^*, x), 0)$. Proposition 4 yield a condition under which a user must stay inactive, as a function of his belief about the probability of future contact opportunities λ , and the message age x . The condition under which a user must become active is determined by the following proposition.

Proposition 5. When the user chooses to sense the channel in search for an access point, if WiFi is not available the 3G connection is used if

$$V(\beta, 1) > V(\beta, x+1) + C_{3G} \quad (5.79)$$

Proof. Let us derive a condition under which the 3G action is optimal. Recall that after sensing the channel in search for an access point, the user updates its message using WiFi if available. Otherwise, the user can wait for another slot ($a = 1$) or use 3G ($a = 2$). We compute a threshold which determines the optimality of $a = 2$ against $a = 1$. To this aim, we compare the expected average reward under the two actions. Given the age x of its message, a mobile user chooses $a = 2$ if and only if $Q_2(\lambda, x) > Q_1(\lambda, x)$,

$$U(x) - E + \lambda(-C + V(\alpha, 1)) + (1 - \lambda)(-C_{3G} + V(\beta, 1)) > \quad (5.80)$$

$$\begin{aligned} U(x) - E + \lambda(-C + V(\alpha, 1)) + (1 - \lambda)V(\beta, x + 1) - \\ -C_{3G} + V(\beta, 1) > V(\beta, x + 1) \end{aligned} \quad (5.81)$$

(5.79) follows from (5.80)-(5.81). \square

Note that, according to Proposition 5, the decision of using 3G is independent of the belief about the probability of a contact opportunity, and depends only on the age x and the 3G cost C_{3G} .

5.6 Numerical results

We now illustrate the applicability of the proposed model through a set of numerical examples. Our goal is to investigate how the various system parameters influence the optimal policy. To this aim, we consider the following system parameters as our reference setting: the maximum age of a message is $M = 12$, the energy cost is $E = 5$, and the costs for using WiFi and 3G are $C = 10$ and $C_{3G} = 300$, respectively.

We consider three scenarios.

- Scenario 1: Access points are most of the time available, $\alpha = 0.8$ and $\beta = 0.3$.
- Scenario 2: Access points are often unavailable, $\alpha = 0.2$ and $\beta = 0.6$.
- Scenario 3: Access points are most of the time available and the cost of 3G is low compared to the previous scenarios, $\alpha = 0.8$, $\beta = 0.3$ and $C_{3G} = 100$.

Figures 5.3, 5.4 and 5.5 show the optimal policies in the three scenarios considered above, obtained using value iteration algorithm (algorithm 1). For each belief λ and age x , a policy determines the probability of adopting each of the available actions. In the three scenarios considered, given a message age x , the optimal policies state that a user must

turn off his mobile device and wait for the next slot if $\lambda < \lambda^*$. Once the threshold is exceeded, the user must sense for an access point looking for a useful contact opportunity.

```

input : The transition probabilities  $\alpha$  and  $\beta$ 
output: The reward matrix  $V$ . Each element  $(\lambda, x)$  of  $V$  is the average reward
         received when the age is  $x$  and the belief  $\lambda$ .

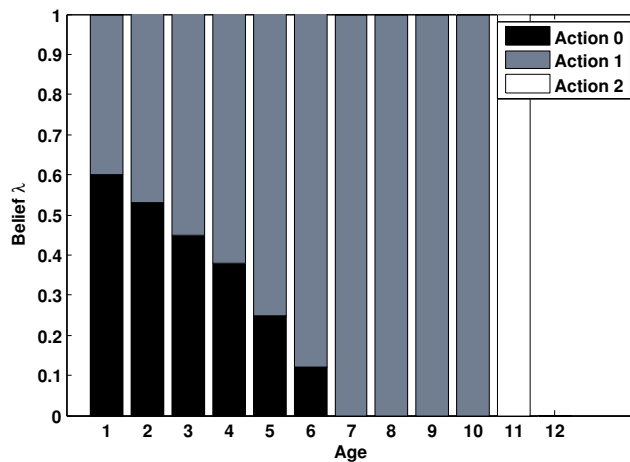
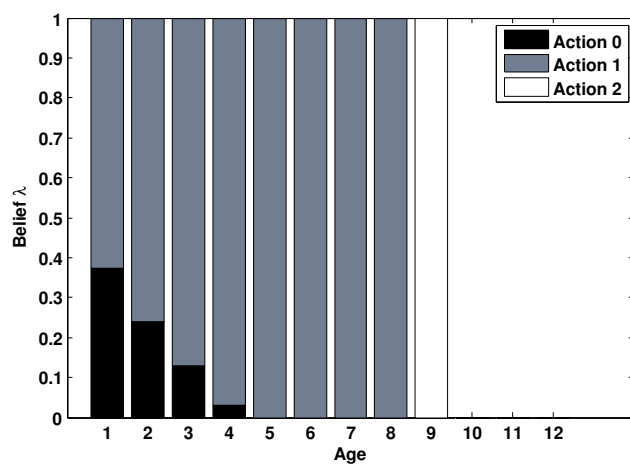
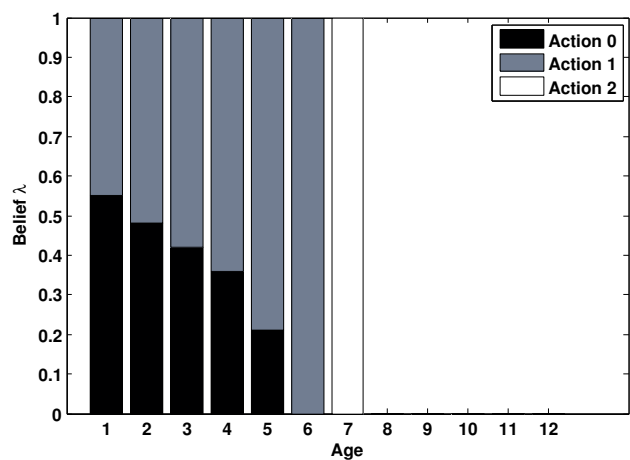
 $\Theta = 1; \lambda \leftarrow \alpha; x \leftarrow 1;$ 
Initialize  $V(\lambda, :)$  and  $V_{new}(\lambda, :)$  as  $M$  dimensional vectors with random elements;
while  $|V - V_{new}| < \xi$  do
   $V \leftarrow V_{new};$ 
  if  $x < M$  then
    Compute  $Q_0(\lambda, x), Q_1(\lambda, x)$  and  $Q_2(\lambda, x)$  using eq. 5.7, 5.8 and 5.9;
     $a \leftarrow \operatorname{argmax}\{Q_a(\lambda, x) : a = 1, 2, 3\};$ 
  else
    Compute  $Q_2(\lambda, x);$ 
     $a \leftarrow 2;$ 
  end
  //Update  $V, V_{new}, \lambda$  and  $x;$ 
   $V_{new}(\lambda, x) \leftarrow Q_a(\lambda, x);$ 
  switch  $a$  do
    case  $a = 0$ 
    |  $\lambda \leftarrow \Omega(\lambda|a)$  using 5.3;  $x \leftarrow \min(x + 1, M);$ 
    case  $a = 1$ 
    |  $r \leftarrow$  random number between 0 and 1;
    | if  $(\Theta = 1 \text{ and } r \leq \alpha)$  or  $(\Theta = 0 \text{ and } r > \beta)$  then
    | |  $\Theta \leftarrow 1; \lambda \leftarrow \alpha; x \leftarrow 1;$ 
    | else
    | |  $\Theta \leftarrow 0; \lambda \leftarrow \beta; x \leftarrow \min(x + 1, M);$ 
    | end
    case  $a = 2$ 
    |  $\lambda \leftarrow \beta; x \leftarrow 1;$ 
  endsw
end

```

Algorithm 1: Computation of the optimal policy (action 2 assumed to be optimal when $x = M$)

As the message age increases, the user is less likely to remain inactive. In addition, the role of the belief λ decreases as the age x increases. In Figures 5.3, 5.4 and 5.5, at ages 11, 9 and 7, respectively, the user decides to sense and transmit using the 3G if the access point is not available (see Proposition 2). Thus, the message age will never surpass these maximum values at the three considered scenarios.

As the access points become less available, is it beneficial to wait for shorter periods of time before activating the mobile devices, as indicated by the decrease of the minimum age to take action 1 when switching from scenario 1 to scenario 2. Finally, in scenario 3 the user is more motivated to use 3G as the 3G cost is reduced.

FIGURE 5.3: Optimal policy for a mobile user where $\alpha = 0.8$, $\beta = 0.3$ and $C_{3G} = 300$ FIGURE 5.4: Optimal policy for a mobile user where $\alpha = 0.2$, $\beta = 0.6$ and $C_{3G} = 300$ FIGURE 5.5: Optimal policy for a mobile user where $\alpha = 0.8$, $\beta = 0.3$ and $C_{3G} = 100$

5.7 Conclusion

In this chapter, we have developed a POMDP framework to study aging control in hybrid wireless networks, taking into account the tradeoff between energy consumption and the age of messages. From the DieselNet measurements, we learned that contact opportunities between users and APs are unpredictable but correlated. We then derived a sensing policy for the aging control problem, and we have shown several propositions satisfied by optimal policies.

We believe this work opens several avenues for future research. While in this work we have studied the aging control problem from the perspective of one single user, future work consists of considering the interaction between several mobile users. Another direction is to consider strategic service providers, that adjust their prices accounting for users that adopt sensing policies as described here.

Part III

On Modeling Multi-hop Wireless Ad hoc Networks

Chapter 6

Layers interactions in IEEE 802.11e-based Multi-hop Ad hoc Networks

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6.1 Introduction

In next-generation wireless networks, it is likely that the IEEE 802.11 wireless LAN (WLAN) will play an important role and affect the style of people's daily life. People want voice, audio, and broadband video services through WLAN connections. Unlike traditional best effort data applications, multimedia applications require quality of service (QoS) support such as guaranteed bandwidth and bounded delay/jitter. There was a lot of interest in modeling the behavior of the IEEE 802.11 DCF (Distributed Coordination Function) and studying its performances in both WLAN networks and multi-hop context. Medium access control protocol has a large impact on the achievable network throughput and stability for wireless ad hoc networks. So far, the ad hoc mode of the IEEE 802.11 standard has been used as the MAC protocols for MANETs. This protocol is based on the CSMA/CA mechanism in DCF.

There have been a number of studies on the performance of IEEE 802.11 in ad hoc networks. All these studies focus on MAC layer without taking into account the routing and the cooperation level of nodes in ad hoc networks, see e.g. [90–96] and [97]. In multi-hop ad hoc networks, the majority of efforts was concentrated to extend Bianchi’s model in saturated or unsaturated network. Now, the problem of hidden terminals and the channel asymmetry are a real issue. A non rare assumption is to consider implicitly symmetric traffic distribution or nodes randomly distributed on a plane following a Poisson point process. Hence, the collision probability and attempt rate are the same for all users. Yang et al. [97] propose an extension of Bianchi [98] and Kumar et al. [99] model, and characterize the channel activities from the perspective of an individual sender. They studied the impact of carrier sensing range and the transmit power on the sender throughput. The PHY/MAC impact was clearly considered. Basel et al. [90] were also interested in tuning the transmit power relatively to the carrier sense threshold. A three dimensional Markov chain was proposed in [100] to derive the saturation throughput of the IEEE 802.11 DCF. The collision probability is now function of the distance between the sender and its receiver. The unsaturated node state was introduced in the Markov chain in [91] and the channel state too. A performance analysis was performed for a single-hop and a multi-hop case considering that a node can carry different traffic load. Medepalli et al. [94] propose an interesting framework model for analyzing the throughput, the delay and fairness characteristics of IEEE 802.11 DCF multi-hop networks. The applicability of the model in terms of network design is also presented.

Our major aim in this chapter is to build a complete framework to analyze multi-hop ad hoc networks under general and realistic considerations. We present a probabilistic but rigorous model incorporating jointly Network, MAC and PHY layers in a simple cross-layer architecture. This latter one has a potential synergy of information exchange among different layers, instead of the standard OSI non-communicating layers. Moreover, we consider the general case of topological asymmetric ad hoc networks in which the nodes have not the same channel perception and then the attempt rate may not always describe the real channel access. Moreover, this model is extended to the IEEE 802.11e which provides differentiated channel access to packets by allowing different rates and different back-off parameters. In order to handle QoS, several traffic classes are also supported. We also allow that each traffic may have different retry limits after which the packet is dropped. From analyzing the model, we find that the performance measures of MAC layer are affected by routing and the traffic intensity of flows to be forwarded. More precisely, the attempt rate and collision probability are now dependent on the traffic flows, topology and routing. Moreover, end-to-end throughput is

independent of cooperation level when all forwarding queues are stable.

6.2 Problem modeling and cross-layer architecture

The network layer of each node i handles two queues. The forwarding queue F_i carries packets originated from some source nodes and destined to some given destinations. The second one is Q_i which carries own packets of node i itself. We assume that the two queues have an infinite storage capacity. Packets are served with a first in first served fashion. When F_i is not empty, the node chooses to send a packet from F_i with a probability f_i , and it chooses to send from Q_i with probability $1 - f_i$. When one of these queues is empty we choose to send from the non empty queue with probability 1. When node i decides to transmit from the queue Q_i , it sends a packet destined to node d , $d \neq i$, with probability $p_{i,d}$. This parameter characterizes somehow the QoS required by the initiated service from upper layers. We consider that each node has always packets to be sent from queue Q_i , whereas F_i maybe empty. Consequently, the network is considered saturated and mainly depends on the channel access mechanism. In ad hoc networks, each node behaves as a router. At each time, it has a packet to be sent to a given destination and starts by finding the next hop neighbor where to transmit the packet. Clearly, each node must carry routing information before sending the packet. Proactive routing protocols as the Optimized Link State Routing construct and maintain a routing table that carries routes to all nodes of the network. To do so, it has to send periodically some control packets. These kind of protocols correspond well with our model, especially since Q_i is non-empty. Here, nodes form a static network where routes between any source s and destination d are invariant. To consider routing in our model, we denote by $R_{s,d}$ the set of nodes between a source s and destination d (s and d not included). Each node in our model can handle many connections on different paths. The traffic flow leaving a node i is determined by the channel allocation using IEEE 802.11 EDCF. However, differentiating the flow leaving F_i and the flow leaving Q_i , allows us to determine the load and the intensity of traffic crossing F_i . We denote here the probability that the forwarding queue F_i is non-empty by π_i . Similarly, we denote the probability that a packet of the path (s, d) is chosen in the beginning of a transmission cycle¹ by $\pi_{i,s,d}$. This quantity is exactly the fraction of traffic related to the path (s, d) crossing F_i , thus $\pi_i = \sum_{s,d:i \neq s} \pi_{i,s,d}$. We analyze in the following each layer separately and show how coupled they are and derive the metrics of interest.

¹A cycle is defined as the number of slots needed to transmit a single packet until its success or drop. It is formed by the four channel events seen by a sender. For instance : idle slots, busy slots, transmissions with collisions and/or a success.

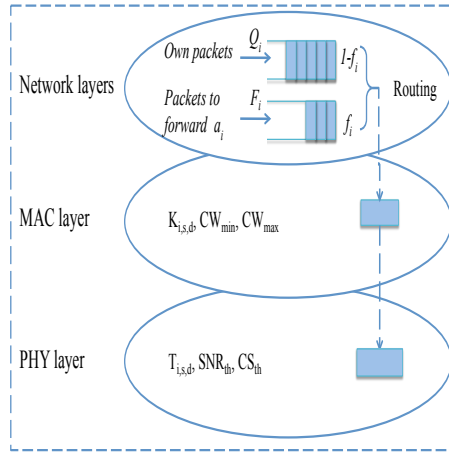


FIGURE 6.1: Interaction between layers

From figure 6.1, we show the interaction between Network, MAC and PHY layers. Attempting the channel begins by choosing the queue from which a packet must be selected. And then, this packet is moved from the corresponding queue at the network layer to the MAC layer where it will be transmitted according to the IEEE 802.11 DCF protocol.

6.2.1 Accumulative Interference and Virtual Node

During a communication between a sender node i and a receiver node j in a given path from s to d (where the source node of a connection is s and the destination node is d), the node i transmits to j with a power $T_{i,s,d}$. The received power on j can be related to the transmitted one by the propagation relation $T_{i,s,d} \cdot h_{i,j}$, where $h_{i,j}$ is the channel gain experienced by j on the link (i,j) . In order to decode the received signal correctly, $T_{i,s,d} \cdot h_{i,j}$ should exceed the receiver sensitivity denoted by RX_{th} , i.e., $T_{i,s,d} \cdot h_{i,j} \geq RX_{th}$. Under symmetry assumption and no accumulative effect of concurrent transmissions, the carrier sense range forms a perfect circle with radius r_1 . Even when considering accumulative interference, the carrier sense can be reasonably approached by a circle with radius $r_2 \geq r_1$.

Definition 6.1. *The group \mathcal{Z} , composed of nodes that cannot be heard individually by a sender i but their accumulative signal may jam the signal of interest, is called a **virtual node**. This way, the virtual node \mathcal{Z} is equivalent to a **fictive node** being in the carrier sense range of sender i .*

We can then formulate the carrier sense set of a node i by the following expression

$$CS_i = \left\{ \mathcal{Z} : \forall s, d, k' \in \mathcal{Z}, \begin{array}{l} \sum_{k \in \mathcal{Z}} T_{k,s,d} \cdot h_{k,i} \geq CS_{th} \\ \sum_{k \in \mathcal{Z} \setminus k'} T_{k,s,d} \cdot h_{k,i} < CS_{th} \end{array} \right\}, \quad (6.1)$$

where CS_{th} is the carrier sense threshold. One can see CS_i as the set of virtual nodes that may be heard by sender i when it is sensing the channel in order to transmit on the path $R_{s,d}$. In other words, CS_i is the set of all real nodes (if they are neighbors of i) and virtual nodes (due to accumulative interferences) that may interfere with node i . Now, we define $H_{i,s,d}$ as the set of nodes that may sense the channel busy when node i is transmitting on the path (s, d) . Then

$$H_{i,s,d} = \{k : T_{i,s,d} \cdot h_{i,k} \geq CS_{th}, \forall s, d\}. \quad (6.2)$$

For sake of clarity, we are restricted in our formulation to the case of single transmission power. However, our model can be straightforward used for studying power control from nodes individual point of views. An interesting feature is that when the transmission power level is the same for all nodes and accumulative interferences are neglected, we have $CS_i = H_{i,s,d}$. *Later result says that under the considered assumptions, the set of nodes heard by node i is exactly the set of nodes that can hear node i when transmitting.* The receiver $j_{i,s,d}$ can correctly decode the signal from sender node i if the Signal to Interference Ratio (SIR) exceeds a certain threshold SIR_{th} . Let the thermal noise variance, experienced on the path (s,d) , be denoted by $N_{i,s,d}$, then

$$SIR_{j_{i,s,d}} = \frac{T_{i,s,d} \cdot h_{i,j}}{\sum_{k \neq i} T_{k,s',d'} \cdot h_{k,j} + N_{i,s,d}} \geq SIR_{th}, \quad \forall s, d, s', d'. \quad (6.3)$$

We define now the interference set of a receiver $j_{i,s,d}$ in a path (s, d) , denoted by $\mathcal{T}_{j_{i,s,d}}$, as the collection of its virtual nodes, i.e., all combination of nodes whose the accumulative signal may cause collisions at $j_{i,s,d}$. For instance, the virtual node \mathcal{Z} is in the interference set of node $j_{i,s,d}$ iff the received signal from node i is completely jammed when nodes in \mathcal{Z} are transmitting all together. The interference set of node j is then written as

$$\mathcal{T}_{j_{i,s,d}} = \left\{ \mathcal{Z} : \begin{array}{l} \frac{T_{i,s,d} \cdot h_{i,j}}{\sum_{z \in \mathcal{Z}} T_{z,s',d'} \cdot h_{z,j} + N_{i,s,d}} < SIR_{th}, \\ \frac{T_{i,s,d} \cdot h_{i,j}}{\sum_{z \in \mathcal{Z} \setminus z'} T_{z,s',d'} \cdot h_{z,j} + N_{i,s,d}} \geq SIR_{th}, \\ \forall z', s', d', z' \neq i, s' \neq s, d' \neq d. \end{array} \right\} \quad (6.4)$$

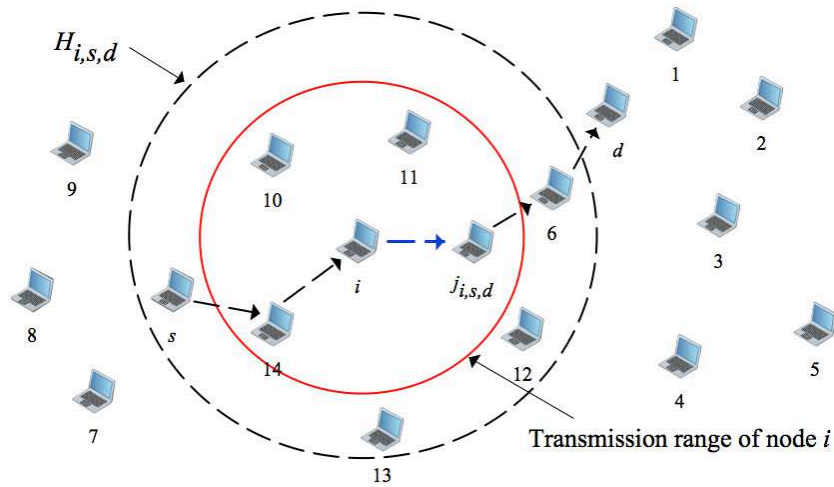


FIGURE 6.2: The plot shows the transmission range of node i and the set of real nodes $H_{i,s,d}$ that can hear i when transmitting to node $j_{i,s,d}$. The carrier sense CS_i of node i and the interference set $\mathcal{T}_{j_{i,s,d}}$ are not plotted because they depend on transmit powers of all nodes in the network as well as the topology and scale of the network. For instance $H_{i,s,d} = \{\{s\}, \{j_{i,s,d}\}, \{6\}, \{10\}, \{11\}, \{12\}, \{13\}, \{14\}, \{7, 8, 9\}, \{d, 4\}, \{1, 5, 7, 8\}, \dots\}$

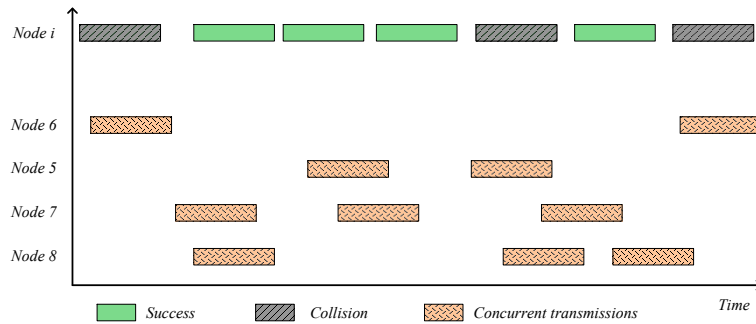


FIGURE 6.3: Effect of accumulative interferences on transmission of node i to node j

Figure 6.2 shows explicitly two different areas that need to be considered when a couple of nodes are communicating. Here, we distinguish (i) the transmission area where two nodes can send and receive packets mutually, (ii) the set of nodes that may hear ongoing transmissions of node i , and (iii) implicitly the carrier sense area where two nodes may hear each other but cannot decode the transmitted data. In Figure 6.3, we have situated the communication of i and j on the path (s, d) , so we can integrate the impact of the routing in the model. Figure 6.3 illustrates the effect of accumulative interference on transmission cycles of node i . For illustrative purpose, we consider the following virtual nodes : $\{6\}$ and $\{5, 7, 8\}$. Node 6 is a neighbor of receiver j which causes collision whenever they both, i.e., nodes i and 6, are transmitting simultaneously. Whereas a failure may only occur when nodes of virtual node $\{5, 7, 8\}$ are all transmitting together with sender i .

Each node uses the IEEE 802.11 DCF to access the channel and each one can use different back-off parameters. Let $K_{i,s,d}$ be the maximum number of retransmissions allowed by a node i per packet on the path (s, d) . Then after $K_{i,s,d}$ number of retransmissions the packet is dropped. Also let p_i be the back-off multiplier of a given node i . The maximum stage number of node i is obtained from $W_{m,i} = p_i^{m_i} W_{0,i}$, where $W_{m,i}$ and $W_{0,i}$ are, respectively, the maximum and initial contention window for node i . If $K_{i,s,d} < m_i$ then m_i takes the value of $K_{i,s,d}$, otherwise $m_i = \log_{p_i} \left(\frac{W_{m,i}}{W_{0,i}} \right)$. Using a contention window $W_{k,i}$ for stage k of node i , the average back-off time for this stage is $b_{k,i}$. Remark that back-off parameters of different nodes may be different. Then, the system of nodes are non-homogeneous as defined by [101].

6.2.2 Attempt Probability and Virtual Slot

We consider the modeling problem of the IEEE 802.11 using the perspective of a sender which consists on the channel activity sensed by a sender, or on the state (success or collision) of its transmitted packet. This will facilitate the problem in the ad hoc environment where nodes have an asymmetric vision of the channel. We start by defining the notion of virtual time slot and channel activity, then we write the expression of the attempt probability for the asymmetric topology. Consider that time is slotted with a physical slot duration τ . Nodes transmit in the beginning of each slot and the transmission duration depends on the kind of the transmitted packet. A data packet has a fixed length and takes *Payload* (integer) slots to be transmitted (it includes the header transmission time). While an acknowledgment packet spends *ACK* slots. On one hand, a sender node before transmitting would see the channel either **busy** or **idle**. On the other hand, its transmitted packet may encounter a **success** or a **collision**. These four states define all the possibilities that a sender may observe. Therefore, the average time spent in a given state (seen by this sender) will be referred as the **virtual slot** of this sender. A remarkable feature here is that this virtual time would depend on the receiver, i.e., on the path where the packet is transmitted. In fact, the success or the collision of the transmitted packet is itself function of the actual receiver interferences state. For that, we denote by $\Delta_{i,s,d}$ the virtual slot seen by node i on the path (s, d) that we will derive later on. Considering any asymmetric topology, we will always note the metrics functions of the path chosen for transmission. We recall that when we mention the node $j_{i,s,d}$, it will be clear that this is the receiver of node i on the path (s, d) .

At steady state and such as [98], we use the key assumption which states that at each transmission attempts, and regardless of the number of retransmissions suffered, each packet collides with constant and independent probability. However, collisions may depend only on the receiver channel state. For that we denote by $\gamma_{i,s,d}$ the probability

that a transmission of a packet of relay i on the path (s, d) fails due to either a corruption of the data or of its acknowledgment. Thus, $(1 - \gamma_{i,s,d})$ is the probability of success in the path (s, d) . Henceforth, the attempt probability seen by a sender also depends on the receiver, and the well known formula of [98] can be used in the ad hoc network as confirmed in [97]. However, in the asymmetric network the attempt probability ($P_{i,s,d}$) (in a virtual slot) for a node i will be different for each path (s, d) and can be written as in [99]:

$$P_{i,s,d} = \frac{1 + \gamma_{i,s,d} + \gamma_{i,s,d}^2 + \dots + \gamma_{i,s,d}^{K_{i,s,d}-1}}{b_{0,i} + \gamma_{i,s,d}b_{1,i} + \gamma_{i,s,d}^2b_{2,i} + \dots + \gamma_{i,s,d}^{K_{i,s,d}-1}b_{K_{i,s,d}-1,i}} \quad (6.5)$$

where $b_{k,i} = (p_i^k W_{0,i} - 1)/2$. In the average, a node i will attempt the channel (for any path (s, d)) with a probability P_i which mainly depends on the traffic and the routing table (here, it is maintained by OLSR protocol). Then

$$P_i = \sum_{s,d:i \in R_{s,d}} \pi_{i,s,d} f_i P_{i,s,d} + \sum_d (1 - \pi_i f_i) p_{i,d} P_{i,i,d}. \quad (6.6)$$

Similarly, the average virtual slot seen by node i is written

$$\Delta_i = \sum_{s,d:i \in R_{s,d}} \pi_{i,s,d} f_i \Delta_{i,s,d} + \sum_d (1 - \pi_i f_i) p_{i,d} \Delta_{i,i,d}. \quad (6.7)$$

Remark 6.2. The attempt probability (or attempt rate) must be differentiated from the transmission probability. This refers to the probability that a node transmits at any slot. Therefore, the transmission probability, if found, can characterize the channel allocation per node. In WLAN, it is sufficient to analyze the back-off rate to determine the channel allocation rate.

The collision probability of a packet occurs when either the data or the acknowledgment experiences a collision. If we note by $\gamma_{i,s,d}^D$ and $\gamma_{j_{i,s,d},s,d}^A$, respectively, the collision probability of a data packet and its acknowledgement, then we have

$$\gamma_{i,s,d} = 1 - (1 - \gamma_{i,s,d}^D) (1 - \gamma_{j_{i,s,d},s,d}^A), \quad (6.8)$$

The attempt probability of a virtual node \mathcal{Z} is defined by $P_{\mathcal{Z}} = \prod_{z \in \mathcal{Z}} P_z$. Therefore, the virtual slot of a virtual node $\Delta_{\mathcal{Z}}$ can be reasonably estimated using the minimum virtual slot among all nodes in \mathcal{Z} , i.e., $\Delta_{\mathcal{Z}} = \min_{j \in \mathcal{Z}} \Delta_j$. Thus the probability that transmitted data collides with other concurrent transmissions can be written as

$$\gamma_{i,s,d}^D = 1 - \prod_{k \in H_{i,s,d} \cap \mathcal{T}_{j_{i,s,d}}} (1 - P_k) \left(1 - \sum_{\mathcal{Z} \in \mathcal{T}_{j_{i,s,d}} \setminus H_{i,s,d}} P_{\mathcal{Z}}^{\frac{\text{Payload}}{\Delta_{\mathcal{Z}}}} \right). \quad (6.9)$$

Indeed, nodes in area $H_{i,s,d} \cap \mathcal{T}_{j,i,s,d}$ must be silent at the beginning of node i transmission. While nodes in $\mathcal{T}_{j,i,s,d} \setminus H_{i,s,d}$ are hidden to i (they constitute the virtual nodes of i) and needs to be silent during all the data transmission time which is a vulnerable time. The $\frac{\text{Payload}}{\Delta_j}$ is the normalized vulnerable time. After the beginning of data transmission, nodes in $H_{i,s,d}$ will defer their transmission to *EIFS* (Extended Inter-Frame Space) duration, which would insure the good reception of the acknowledgment. In practice, acknowledgements are small packets and less vulnerable to collision, for that it is plausible to consider $\gamma_{j,i,s,d,s,d}^A \simeq 0$. Then, we can write $\gamma_{i,s,d} = \gamma_{i,s,d}^D$.

Considering the previously defined four states and from node i view, the network stays in a single state a duration equal to $\Delta_{i,s,d}$. It's given by

$$\Delta_{i,s,d} = P_{i,s,d}^{succ} \cdot T_{succ} + P_{i,s,d}^{col} \cdot T_{col} + P_i^{idle} \cdot T_{idle} + P_i^{busy} \cdot T_{busy}, \quad (6.10)$$

$$\text{where } \begin{cases} T_{succ} = \text{Payload} + \text{ACK} + \text{SIFS} + \text{DIFS}, \\ T_{col} = \text{Payload} + \text{ACK} + \text{DIFS}, \\ T_{idle} = \tau, \\ T_{busy} = \text{Payload} + \text{DIFS}, \\ P_{i,s,d}^{succ} = P_{i,s,d}(1 - \gamma_{i,s,d}), \\ P_{i,s,d}^{col} = P_{i,s,d}\gamma_{i,s,d}, \\ P_i^{idle} = \prod_{Z \in CS_i \cup \{i\}} (1 - P_Z), \\ P_i^{busy} = (1 - P_i) \sum_{Z \in CS_i} P_Z. \end{cases} \quad (6.11)$$

Finally, let us denote the equations (6.5), (6.6), (6.8) and (6.10) by *system I*. Normally, it is sufficient to solve the *system I* to derive the fixed points of each node. However, by introducing the traffic metric in equations (6.6) and (6.7), these equations cannot be solved without knowing the $\pi_{i,s,d}$ which is defined as the traffic intensity for each path (s, d) crossing node i . Therefore, in Section 6.3, we proceed in writing the rate balance equations at each node, from which $\pi_{i,s,d}$ can be derived as a function of P_j and $\gamma_{j,s,d}$, for all j . These rate balance equations give the traffic intensities. The problem resides in the complexity of the systems and in the computational issue.

6.3 End-to-end throughput and traffic intensity system

We are interested in this section to derive the end-to-end throughput per connection, function of different layer parameters, including the IEEE 802.11 parameters. It is clear that the average performance of the system is hardly related to the interaction PHY/MAC/NETWORK. We focus now on the traffic crossing the forwarding queues,

which may be an issue on the buffers stability. We say that a queue F_i is stable if the departure rate of packets from F_i is equal to the arrival rate into it. This is a simple definition of stability that can be written with a *rate balance equation*. We are going to derive this equation for each node i and each connection (s, d) . The system of these equations, for all i and (s, d) , will form the traffic intensities system, it will be referred as *system II*. In sum, we are writing a system that determines $\pi_{i,s,d}$ for all i and (s, d) . For that, we first derive the average length of a transmission cycle per packet C_i at node i . A cycle length on the path $R_{s,d}$ is formed by the attempt slots that do not lead to a channel access, to a transmission and to a retransmissions of the same packet until a success or a drop. A cycle may contain idle periods, busy periods, collision periods or/and at most one successful transmission period. Let the random variable (r.v.) X_i (resp. Y_i , Z_i and V_i) be the number of idle periods (resp. the number of busy periods, the number of collision periods and the number successful periods) in a cycle on the path $R_{s,d}$. Hence the average length in slots of this cycle is given by

$$\begin{aligned} \hat{C}_{i,s,d} &= \sum_{k=1}^{K_{i,s,d}-1} \sum_{l=0}^{\infty} \sum_{h=0}^{\infty} \binom{l+h+k}{l} \binom{h+k}{h} \\ &\times (l.T_{idle} + h.T_{busy} + k.T_{col} + T_{succ}).Pr_{l,h,k,1} \\ &+ \binom{l+h+K_{i,s,d}-1}{l} \binom{h+K_{i,s,d}-1}{h} \\ &\times (l.T_{idle} + h.T_{busy} + K_{i,s,d}.T_{col}).Pr_{l,h,K,0}, \end{aligned} \quad (6.12)$$

where $Pr_{l,h,k,j} = (P_i^{idle})^l (P_i^{busy})^h (P_{i,s,d}^{col})^k (P_{i,s,d}^{succ})^j$. When a node transmits to several paths, we need to know the average cycle length. Hence, the average cycle of a node is given by

$$C_i = \sum_{s,d:i \in R_{s,d}} \pi_{i,s,d} f_i \hat{C}_{i,s,d} + \sum_d (1 - \pi_i f_i) p_{i,d} \hat{C}_{i,i,d}. \quad (6.13)$$

To write the departure rate from F_i as well as the arrival rate into it, let us first consider the following counters :

- $C_{t,i}$ is the number of cycle of the node i till the t^{th} slot, where t slots means t physical slots and it is equivalent to $t.\delta$ seconds with $\delta = 20\mu s$ in the IEEE 802.11.
- $C_{t,i}^F$ (resp. $C_{t,i}^Q$) is the number of all *forwarding cycles* (resp. *source cycles*) of the node i till the t^{th} slot.
- $C_{t,i,s,d}^F$ (resp. $C_{t,i,s,d}^Q$) is the number of *forwarding cycles* (resp. *source cycles*) corresponding to the path $R_{s,d}$ of the node i till the t^{th} slot.

- $T_{t,i,s,d}$ is the number of times we found at the first slot of a cycle and at the first position in the queue F_i a packet for the path $R_{s,d}$ of the node i till the t^{th} slot.
- $I_{t,i,s,d}$ is the number of cycles corresponding to the path $R_{s,d}$ of the node i , where a cycle is ended by a success of the transmitted packet till the t^{th} slot.
- $A_{t,i,s,d}$ is the number of arrival packets to node i on the path $R_{s,d}$.

Departure rate : The departure rate from F_i is the probability that a packet is removed from node i (forwarding queue) by either a successful transmission or a drop after successive $K_{i,s,d}$ failures. The departure rate concerning only the packets sent on the path $R_{s,d}$ is denoted by $d_{i,s,d}$. Formally, for any node i , s and d such that $p_{s,d} > 0$ and $i \in R_{s,d}$, the long term departure rate of packets from node i on the route from s to d is given by the following theorem

Theorem 6.3.1. The long term departure rate from node i related to path $R_{s,d}$ is given by

$$d_{i,s,d} = \frac{f_i \pi_{i,s,d}}{C_i}. \quad (6.14)$$

Proof. The long term departure rate of packets from node i on the route from s to d is

$$d_{i,s,d} = \lim_{t \rightarrow \infty} \frac{C_{t,i,s,d}^F}{t} = \lim_{t \rightarrow \infty} \frac{T_{t,i,s,d}}{C_{t,i}} \cdot \frac{C_{t,i,s,d}^F}{T_{t,i,s,d}} \cdot \frac{C_{t,i}}{t}. \quad (6.15)$$

- $\lim_{t \rightarrow \infty} \frac{T_{t,i,s,d}}{C_{t,i}}$ is the probability that F_i carries a packet to the path $R_{s,d}$ at the beginning of each cycle. Therefore $\lim_{t \rightarrow \infty} \frac{T_{t,i,s,d}}{C_{t,i}} = \pi_{i,s,d}$.
- $\lim_{t \rightarrow \infty} \frac{C_{t,i,s,d}^F}{T_{t,i,s,d}}$ is exactly the probability that we have chosen a packet from F_i to be sent when F_i carried a packet to the path $R_{s,d}$ in the first position and in the beginning of a forwarding cycle. Therefore, $\lim_{t \rightarrow \infty} \frac{C_{t,i,s,d}^F}{T_{t,i,s,d}} = f_i$.
- $\lim_{t \rightarrow \infty} \frac{t}{C_{t,i}}$ is the average length in slots of a cycle of the node i . Moreover, we have

$$d_{i,s',d'} = \frac{\pi_{i,s',d'} f_i}{\sum_{s,d:i \in R_{s,d}} \pi_{i,s,d} f_i \hat{C}_{i,s,d} + \sum_d (1 - \pi_i f_i) p_{i,d} \hat{C}_{i,i,d}}. \quad (6.16)$$

Hence from (6.13), it is easy to derive the total departure rate d_i on all paths:

$$d_i = \sum_{s',d':i \in R_{s',d'}} d_{i,s',d'} = \frac{\pi_i f_i}{C_i}. \quad (6.17)$$

□

Arrival rate and end-to-end throughput : The probability that a packet arrives to the queue F_i of the node i is also called the arrival rate, we denote it by a_i . When this rate concerns only packets sent on the path $R_{s,d}$, we denote it by $a_{i,s,d}$. Formally, for any nodes i, s and d such that $p_{s,d} > 0$ and $i \in R_{s,d}$, the long term arrival rate of packets into F_i for $R_{s,d}$ is provided by the following theorem

Theorem 6.3.2. The long term arrival rate into node i forwarding queue, related to path $R_{s,d}$, is given by

$$a_{i,s,d} = (1 - \pi_s f_s) \cdot \frac{p_{s,d}}{C_s} \cdot \prod_{k \in R_{s,i} \cup s} \left(1 - \gamma_{k,s,d}^{K_{k,s,d}}\right). \quad (6.18)$$

Proof. The long term arrival rate of packets into F_i for $R_{s,d}$ is

$$a_{i,s,d} = \lim_{t \rightarrow \infty} \frac{A_{t,i,s,d}}{t} = \lim_{t \rightarrow \infty} \frac{C_{t,s}^Q}{C_{t,s}} \cdot \frac{C_{t,s,s,d}^Q}{C_{t,s}^Q} \cdot \frac{C_{t,s}}{t} \cdot \frac{I_{t,s,s,d}}{C_{t,s,s,d}^Q} \cdot \frac{A_{t,i,s,d}}{I_{t,s,s,d}}. \quad (6.19)$$

- $\lim_{t \rightarrow \infty} \frac{C_{t,s}^Q}{C_{t,s}} = 1 - \frac{C_{t,s}^F}{C_{t,s}} = 1 - \pi_s f_s$ is exactly the probability to get a source cycle, i.e., to send a packet from the queue Q_s .
- $\lim_{t \rightarrow \infty} \frac{C_{t,s,s,d}^Q}{C_{t,s}^Q}$ is the probability to choose the path $R_{s,d}$ to send a packet from Q_s .
Therefore, $\lim_{t \rightarrow \infty} \frac{C_{t,s,s,d}^Q}{C_{t,s}^Q} = p_{s,d}$.
- $\lim_{t \rightarrow \infty} \frac{C_{t,s}}{t} = \frac{1}{C_s}$.
- $\lim_{t \rightarrow \infty} \frac{I_{t,s,s,d}}{C_{t,s,s,d}^Q}$ is the probability that a source cycle on the path $R_{s,d}$ ends with a success, i.e., the packet sent from Q_s is received on the queue $F_{j_{s,s,d}}$. Therefore, $\lim_{t \rightarrow \infty} \frac{I_{t,s,s,d}}{C_{t,s,s,d}^Q} = 1 - \gamma_{s,s,d}^{K_{s,s,d}}$.
- $\lim_{t \rightarrow \infty} \frac{A_{t,i,s,d}}{I_{t,s,s,d}}$ is the probability that a packet received on the node $j_{s,s,d}$ is also received on the queue F_i of the node i . For that, this packet needs to be received by all the nodes in the set $R_{s,i} \cup s$. Therefore, $\lim_{t \rightarrow \infty} \frac{A_{t,i,s,d}}{I_{t,s,s,d}} = \prod_{k \in R_{s,i} \cup s} \left(1 - \gamma_{k,s,d}^{K_{k,s,d}}\right)$.

Consequently, the result of the theorem holds. \square

End-to-end throughput : The global arrival rate at F_i is $a_i = \sum_{s,d:i \in R_{s,d}} a_{i,s,d}$. Remark that when the node i is the final destination of a path $R_{s,d}$, then $a_{d,s,d}$ represents the end-to-end average throughput of a connection from s to d . Practically, $a_{d,s,d}$ is the

number of delivered (to destination) packet per slot. Let ρ be the bit rate in bits/s of the wireless network. Therefore, the throughput in bits/s can be written as follows:

$$thp_{s,d} = a_{d,s,d} \cdot \text{Payload} \cdot \rho. \quad (6.20)$$

Rate balance equations/traffic intensity system : Finally, in the steady state if all the queues in the network are stable, then for each i , s and d such that $i \in R_{s,d}$ we get $d_{i,s,d} = a_{i,s,d}$, which is the rate balance equation on the path $R_{s,d}$. For all i , s and d we get the traffic intensity system: *system II*. And when we sum the both sides of this last system, we get the global rate balance equation: $d_i = a_i$.

Let $y_i = 1 - \pi_i f_i$ and $z_{i,s,d} = \pi_{i,s,d} f_i$. Thus $y_i = 1 - \sum_{s,d:i \in R_{s,d}} z_{i,s,d}$. Then, the rate balance equation can be written in the following form:

$$\sum_{d:i \in R_{s,d}} z_{i,s,d} = \frac{y_s (\sum_{s',d'} z_{i,s',d'} \hat{C}_{i,s',d'} + \sum_{d''} y_i p_{i,d''} \hat{C}_{i,i,d''}) w_{s,i}}{(\sum_{s',d'} z_{s,s',d'} \hat{C}_{s,s',d'} + \sum_{d''} y_s p_{s,d''} \hat{C}_{s,s,d''})}, \quad (6.21)$$

where $w_{s,i} = \sum_{d:i \in R_{s,d}} p_{s,d} \prod_{k \in R_{s,i} \cup s} (1 - \gamma_{k,s,d}^{K_{k,s,d}})$.

An interesting interpretation and application of equation (6.21) are the following : (i) $z_{i,s,d}$ and y_i (can be considered as the stability region of node i) are independent of the choice of f_i . (ii) For some values of f_i the forwarding queue of node i will be stable. Concerning P_i , we notice that it can be written as $P_i = \sum_{s,d:i \in R_{s,d}} z_{i,s,d} P_{i,s,d} + \sum_d y_i p_{i,d} P_{i,i,d}$. Then it depends on $z_{i,s,d}$ and y_i , but it is not affected by f_i .

Resolving PHY/MAC/NETWORK coupled problems : As we showed previously, the MAC layer systems of fixed points and the Network layer rate balance systems (non linear systems) could not be resolved separately. Moreover, due to dependance on topology, routing and users behaviors, we cannot show analytically existence of a unique solution of the fixed point systems. However, for several scenarios and network topologies, *system I* and *system II* always provide the same solution as obtained from simulation. We give in algorithm 2 a sketch of the algorithmic way we follow to solve mutually the above systems (including the correlation between layers).

Special Cases : For sure the *system I* and *system II* are complicated to solve and computational expensive. For that, special cases are important and would facilitate the analysis of the systems and can be useful and easy to use in numerical results. As we have mentioned previously, $P_{i,s,d}$ and $\gamma_{i,s,d}$ need to be found jointly with $\pi_{i,s,d}$. This is due to the traffic asymmetry. Furthermore, the average cycle length C_i is function of $\pi_{i,s,d}$. This also complicate the calculation of $\pi_{i,s,d}$, when $P_{i,s,d}$ and $\gamma_{i,s,d}$ are given. Therefore, two special cases can be distinguished as following:

Require: $\pi_{i,s,d}^0 = \epsilon_{i,s,d}$, δ : convergence indicator

- 1: **for** each source s , relay i and destination d **do**
- 2: **while** $\left| \frac{\pi_{i,s,d}^{t+1} - \pi_{i,s,d}^t}{\pi_{i,s,d}^t} \right| \geq \delta$ **do**
- 3: Compute $P_{i,s,d}$ using fixed point such as [99]
- 4: Update $\gamma_{i,s,d}$ using equation (6.9)
- 5: Estimate cycles size using equation (6.13)
- 6: Update $\pi_{i,s,d}^{t+1}$ by solving the rate balance system (6.21) using for example the Gaussian elimination method
- 7: **end while**
- 8: **end for**

Algorithm 2: Fixed point and rate balance resolution

- Uniform traffic distribution and symmetric topology: $\gamma_{i,s,d} \equiv \gamma_i$ and $P_{i,s,d} \equiv P_i$.
Also, $C_i \equiv \hat{C}_{i,s,d}$.
- Uniform traffic distribution and asymmetric topology: $\gamma_{i,s,d} \neq \gamma_i$ and $P_{i,s,d} \neq P_i$.
Also, $C_i \neq \hat{C}_{i,s,d}$, except the case where the routing at each node chooses the same next hop to route packets for all paths (s, d) .

In these two cases, the *System I* is independent of $\pi_{i,s,d}$, i.e., *System I* and *system II* are decoupled. Therefore, we can find the attempt and collision probabilities in *System I*, and then calculate the traffic intensity. In addition, the *system II* becomes a linear system that can be solved easily.

In addition, *system I* will be simplified when no hidden nodes are found in the network. This case can happen when the interference area of receivers j is included in the carrier sense area of each sender i , i.e., $I_j \setminus CS_i = \emptyset$. This imply that $\gamma_{i,s,d}$ will be independent of the virtual slot $\Delta_{i,s,d}$.

6.4 Simulation and numerical investigations

We turn in this section to study a typical example of multi-hop ad hoc networks. We consider an asymmetric network formed by 9 nodes, identified using an integer from 1 to 9 as shown in Fig. 6.4. We establish 9 connections (or paths) labeled by a letter from a to i . Each node is located by its plane Cartesian coordinates expressed in meters. Except contraindication, the main parameters are fixed to the following values : $CW_{min} = 32$, $CW_{max} = 1024$, $K_{i,s,d} \equiv K = 4$, $f_i \equiv f = 0.9$ (to insure stability of forwarding queues), $T_{i,s,d} \equiv T = 0.1W$ ($\forall i, s, d$), $CS_{th} = 0$ dBm, $RX_{th} = 0$ dBm, $SIR_{th} = 10$ dB (target SIR), $\rho = 2$ Mbps (bit rate), $\alpha = 2$ (path loss exponent factor), $c = 6$ dBi (antenna gain), $\delta = 20\mu s$ (physical slot duration), $DIFS = 3\delta$ and $SIFS = \delta$.

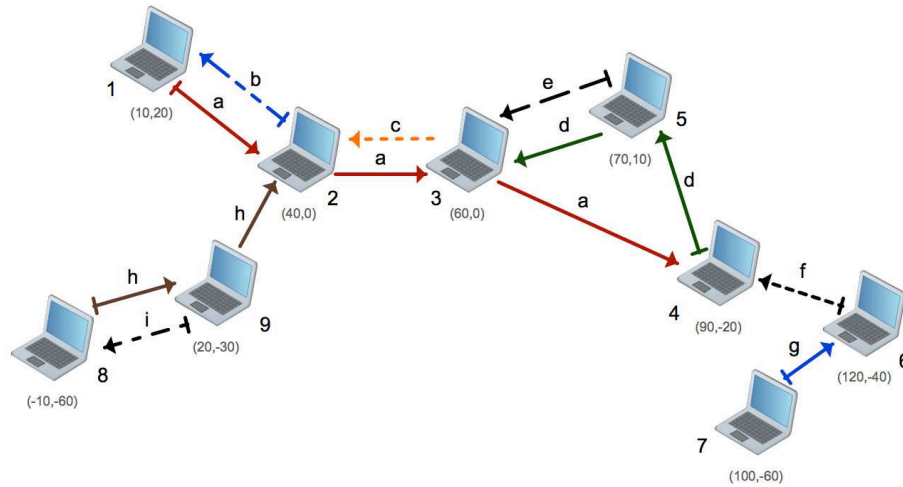


FIGURE 6.4: The multi-hop wireless ad hoc network used for simulation and numerical examples.

Model validation : We now present extensive numerical and simulation results to show the accuracy of our model and then study the impact of joint PHY, MAC and NETWORK parameters. For that aim, a discrete time simulator that implements the IEEE 802.11 DCF, integrating the weighted fair queueing over the two buffers previously discussed, is used to simulate the former network. Each simulation is realized during 10^6 physical slots, repeated at least 20 times and then averaged to smooth out the fluctuations caused by random numbers generator of the simulator. We checked the validity of the model by extensively considering different network scenarios and topologies. We depict in Fig. 6.5 (resp. Fig. 6.6) the analytic as well as the simulative average load of forwarding queues (resp. average end-to-end delay of considered connections). Numerical plots show that analytic model match well with simulative results, in particular under the stability region which is the main applicability region of our model. With some abuse we refer to the interval of forwarding probability that insure a load strictly less than 1 for all queues, as the stability region. The main difference seen between individual loads is mainly due to the topology asymmetry. Based on Fig. 6.6, we note that our analytic finding saying that under the stability condition, the end-to-end throughput does not depend on the choice of the WFQ weight, i.e., the cooperation level or forwarding probability. Therefore, one can judiciously fine-tune the cooperation level value to decrease the delay when the average throughput is kept almost constant. This mechanism may play a crucial role in delay sensitive traffic support over multi-hop networks. Later, we plot the average throughput versus the normalized payload size (the number of slots required to transmit a packet). We conclude from Fig. 6.7 that an optimal payload size may not exist. Indeed, we note that some specific payload size is providing good performances in term of average throughput over some paths, but may hurt drastically the throughput of other links and then the reachability becomes a real

issue. Setting the payload size to a fixed value over the whole network is, in general, unfair and is not suitable for multi-hop networks. However fortunately, existence of locally optimal payload size may exist. This way, it depends strongly on the topology and the local node densities, i.e., the number of neighbors, their respective distances with respect to a tagged node and how they are distributed in the network. Fig. 6.8 shows the variation of average loads of intermediate nodes as a function of the normalized payload. Here, π_i is strictly decreasing for all nodes i . This provides an intuition to limit the forwarding queues load (equivalently the delay) by setting the payload size to a high value. Unfortunately, this is unfair and may hurt some connections with more penalizing environment and bad channel state.

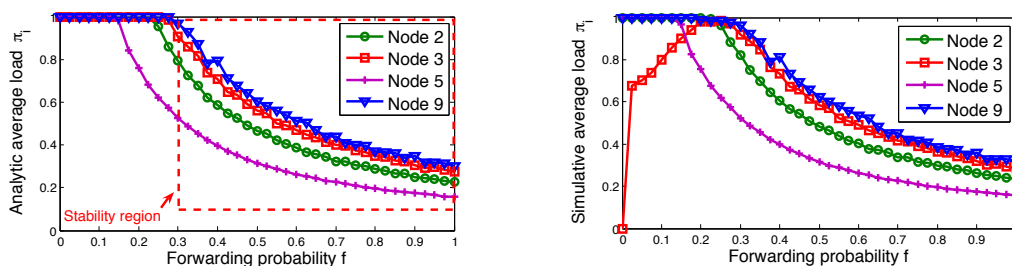


FIGURE 6.5: Average forwarding queues load from model versus simulation as function of forwarding probability.

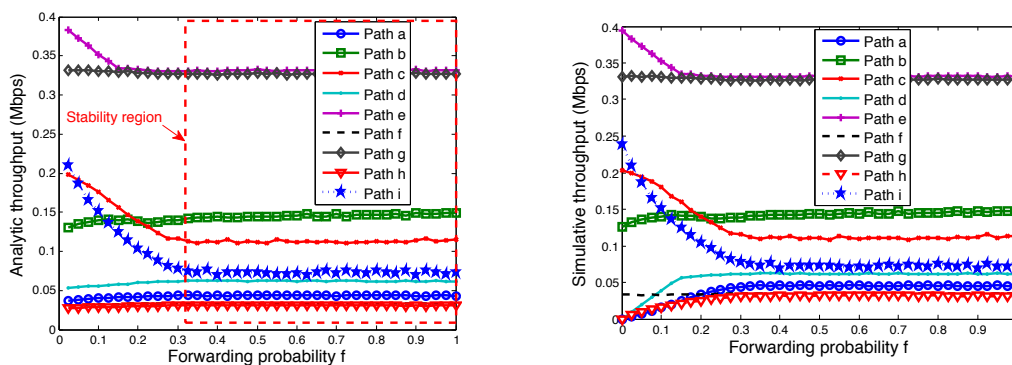


FIGURE 6.6: Average end-to-end throughput from model versus simulation as function of forwarding probability.

Fig. 6.9 plots the average throughput experienced by all established connections when varying the minimum contention window CW_{min} . We remark that the throughput behaves in two different ways according to the topology of the multi-hop network. Indeed, when the nodes density is low, the throughput is maximized for short backlog duration (connections e , g and i). Here, nodes take advantage from local nodes density and tend to transmit more aggressively, having a relatively low collision probability due to low number of competitors. Whereas for other connections, the optimal contention windows size is different from CW_{min} defined by the IEEE 802.11 DCF standard. We also note that contention windows tends to increase as the nodes density becomes high. This latter

remark is quite intuitive and due to the fact that the competitions becomes colossal. In terms of queues load (equivalently delay), it is clear that when the contention windows increases it implies the increase of queues load and henceforth tagged node may suffer from huge delay.

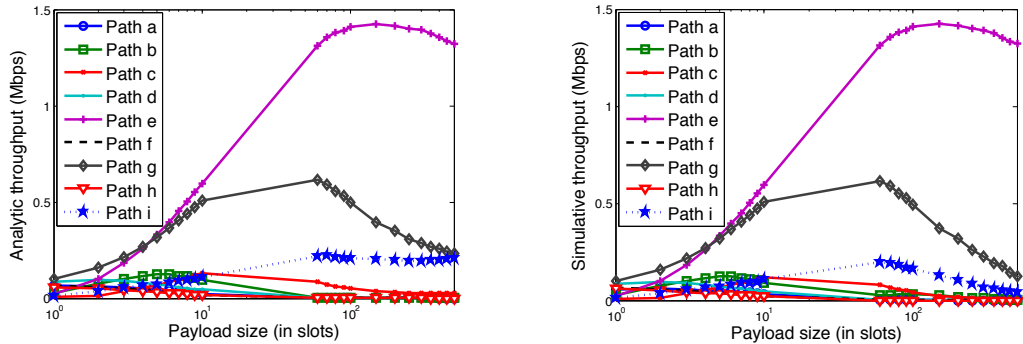


FIGURE 6.7: Average end-to-end throughput from model versus simulation when varying the payload size.

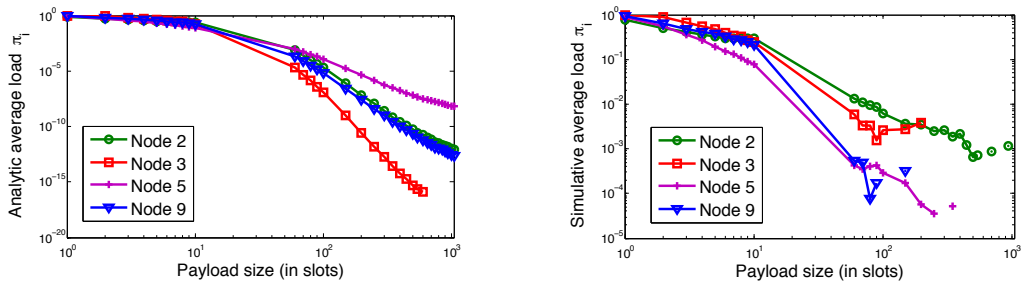


FIGURE 6.8: Average load of forwarding queues from model versus simulation when varying the payload size.

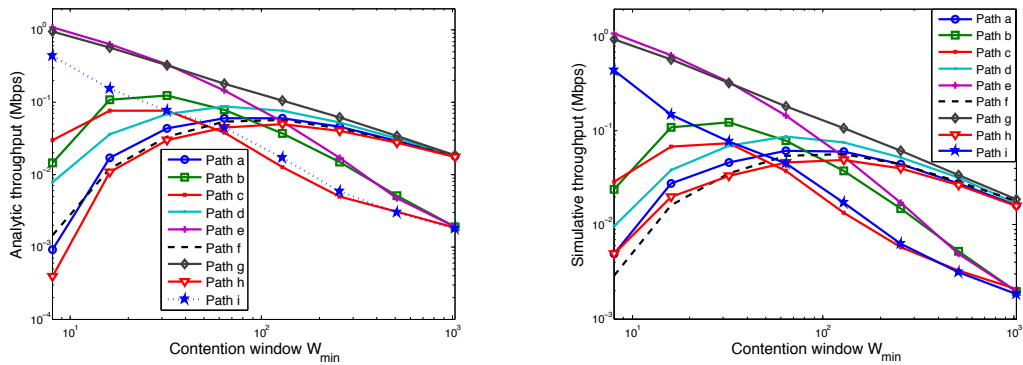


FIGURE 6.9: Average end-to-end throughput from model versus simulation when varying the minimum contention window.

Per path power and carrier sense control : We reconsider here the Spanning tree-based algorithm proposed in [102]. Each node sets its transmit power to a level that allows reaching the farthest neighbor, i.e. the received power is at least equal to the receiver sensitivity. Consequently, this per path power control may improve the spatial reuse. In order to analyze the impact of carrier sense threshold on network performances,

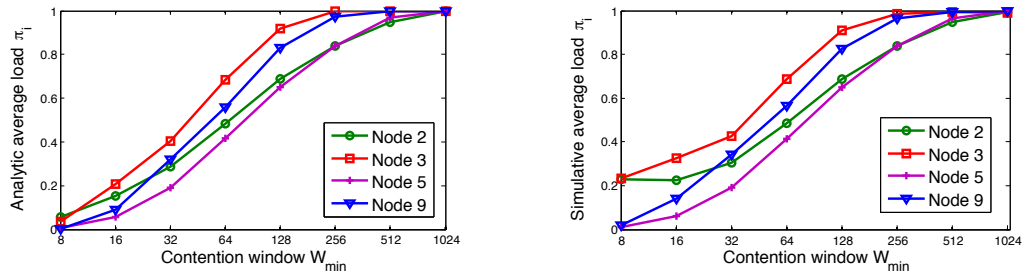


FIGURE 6.10: Average load of forwarding queues from model versus simulation when varying the minimum contention window.

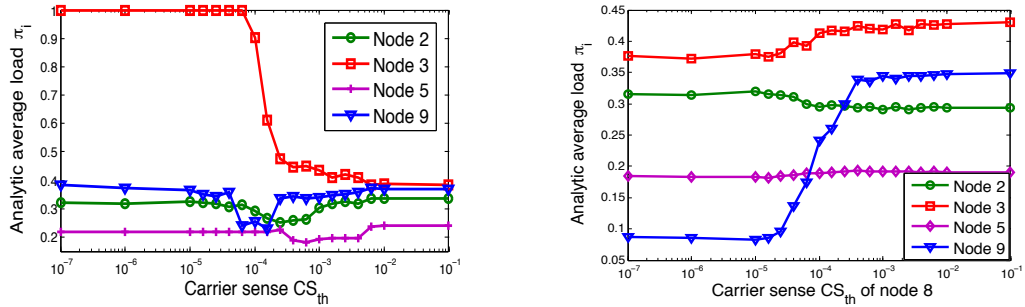


FIGURE 6.11: Average load of forwarding queues from model versus simulation for variable carrier sense threshold (in Watt).

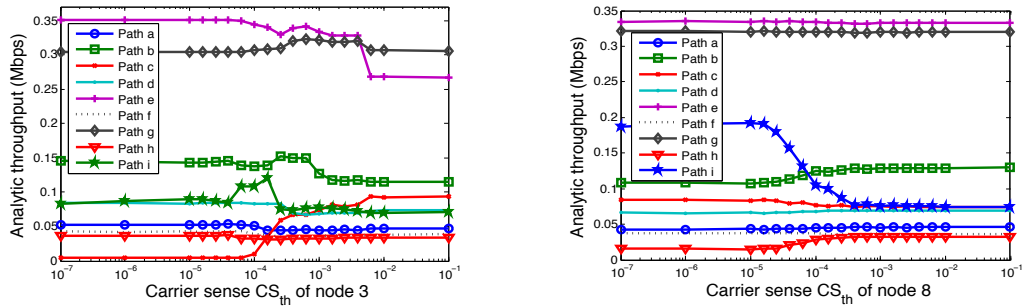


FIGURE 6.12: End-to-end throughput from model versus simulation for variable carrier sense threshold (in Watt).

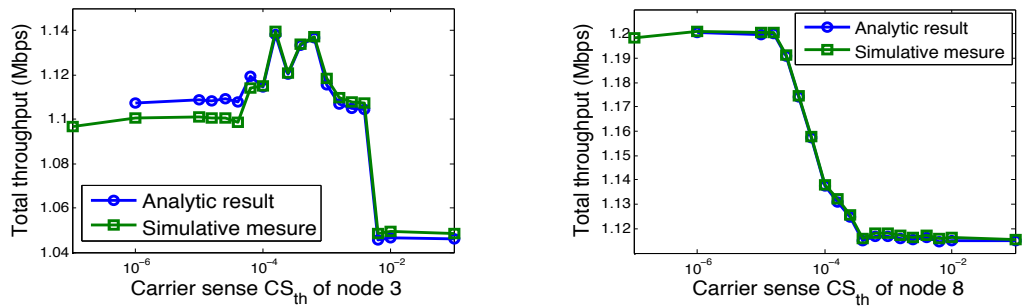


FIGURE 6.13: End-to-end throughput from model versus simulation for variable carrier sense threshold (in Watt).

we will vary CS_{th} for some tagged node and fix it to the default value, i.e., $CS_{th} = 0$ dBm. We plot in Fig. 6.12 the average throughput of all paths when varying the carrier sense threshold of node 3 which is located in a relatively dense subnetwork. We note that the throughput of all connections continues to decrease (in particular connections crossing node 3 or its immediate neighbors) with CS_{th} except connections originated from node 3. Now we analyze the interplay of node 8 (in a low dense subnetwork) carrier sense on network performances. We note that the only negatively impacted connection is connection i originated from node 9 (immediate neighbor of node 8). When carrier sense of node 8 is increasing, it becomes more nose-tolerable which imply a more transmission aggressiveness. Which explain the throughput decrease of connection i due to larger backoff duration of node 9 to resolve collision. Thus connections crossing neighbors of node 9 take advantage from the low attempt rate of node 9 to improve their throughput, for instance connections a , b and h .

Aggregate throughput : In terms of total capacity and depending on the local nodes density, the carrier sense control may increase the network throughput. Indeed, when a node in a dense zone fine-tunes its carrier sense threshold, we note existence of a region where the total capacity is maximized. This region correspond to a CS_{th} interval where tagged node benefits from relatively high throughput and other nodes don't suffer much from this. Whereas, it seems that allowing nodes in low dense parts of the network may cause a throughput decrease due to selfishness of tagged nodes. To sum up, we can say that on one hand, a higher carrier sense threshold encourages more concurrent transmissions but at the cost of more collisions. On the other hand, a lower carrier sense threshold reduces the collision probability and prevents simultaneous transmissions from occurring, which may result in limiting the system throughput.

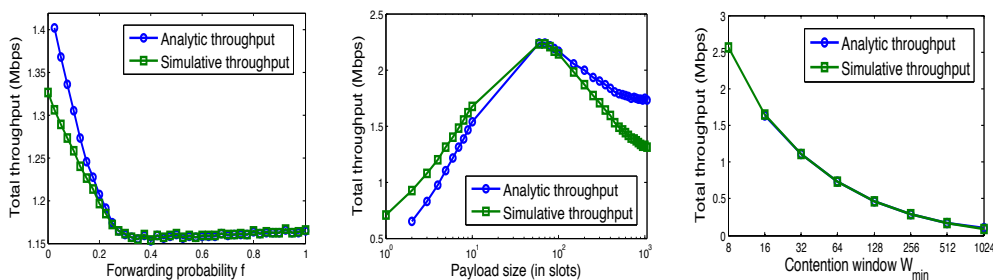


FIGURE 6.14: Average cycle size from model versus simulation under different parameters variation.

6.5 Conclusion

In contrast to classical systems where all users communicate with an access point and have, in general, the same channel/environment view. In ad hoc networks, the main

difference is the variable topology and the asymmetric view. A judicious and punctual solution is to auto-configure parameters of the PHY/MAC/NETWORK by the node itself. However unfortunately, this may result in a performance collapse due to users selfishness (similar to prisoners dilemma in game theory). We also suggest to run a MAC/PHY cross-layer control where each node is increasing the transmit power whenever a retransmission is needed. Unfortunately, this power control seems to be unfair since the benefit is strongly depending on the topology. Due to asymmetry, many nodes take benefit from this policy but others may hardly suffer from it. To sum up, under topology asymmetry, the problem is not how to choose parameters such as how the network may operate in optimal way; but the problem is how to define a cooperation level and a trade-off between end-to-end throughput and delay.

Analyzing Fig. 6.14 where the behavior of the total capacity is depicted as a function of nodes intrinsic parameters (f_i , $Payload_i$ and CW_i), we note that the capacity is maximal when node behave selfishly, i.e., $f = 0$. A high amount of traffic in the topology of Fig. 6.4 is issued from one hop paths, which explains the continuous decrease of the capacity with cooperation level f . However, the cooperation is crucial to maintain the network connectivity. In a game theory view and under node rationality assumption, if a node refuses to forward packets of neighboring nodes then the other may behave similarly. As a result the total capacity may fall down drastically and delay may go to infinity (very large waiting time in intermediate buffers). A challenging but promising concept is then to enable an autonomous location and environment-aware feature. Here, each node may sense the channel, learn the channel state/network topology, decide the best setup, adapt its parameters and reconfigure them till desired QoS is achieved. Nodes can then share their respective information for better environment awareness and less signaling traffic.

In this chapter we have studied a multi-hop ad hoc network, where a stack of protocols would interact with each other to accomplish a successful packet transfer. In this context, we have developed a cross-layered model built on the IEEE 802.11e EDCF standard. We studied the effect of forwarding on end-to-end performances. We have discovered that the modeling of the IEEE 802.11 in this context is not yet mature in the literature and to the best of our knowledge, there is no study done that considers jointly the PHY/MAC/NETWORK interaction in a non-uniform traffic and a general network topology. This has led us to build a general framework using the perspective of individual senders. The attempt and collision probabilities are now functions of the traffic intensity, on topology and on routing decision. The fixed point *system I* is indeed related to the traffic intensity *system II*. This opens many interesting directions to study in future such as power control and delay-based admission control with guaranteed throughput.

Chapter 7

Conclusion and Perspectives

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7.1 Summary of contributions

In this dissertation, we have covered different aspects of analysis, design, and optimization of protocols and architectures for heterogeneous wireless access networks. We were interested first, to design a QoS framework in multiple cognitive wireless networks, where each WSP is independent from the others. We have proposed two dynamic access control schemes, and studied their impact on the overall performance of SUs. The model developed describes the interaction between users in one side, and between users and service providers in the other side. Based on a Markov process, we were able to propose an approximation to the exact solution to make the problem much easier to solve, without changing its characteristics. Furthermore, this approximation is more realistic in this context, since a service provider has only partial information about the system. This latter can allow to virtual providers to use its resources. We were interested to how a virtual provider can determines the optimal amount of bandwidth he has to lease from the spectrum owner. Indeed, we have considered the revenue maximization problem in a MVNO with self-interested mobile users. A model without interference where the provider supplies different bandwidth frequencies to different users was first considered, and then extended to support interference between users. We have proposed a near-optimal solution with respect to users strategy, interference and bandwidth management. Furthermore, a more general model using a POMDP framework to illustrate

the case where the provider doesn't have complete information about the channel state of all users was studied. Optimal policy to follow by the provider to maximize his revenue based on a belief vector was found.

Thereafter, we have focused on delay tolerant networks, where mobile users have the choice between many access technologies (WiFi and 3G in our study). First, we learned from DieselNet measurements, that correlations among contact opportunities do not play a key role if the energy costs incurred by users are small, or if users cannot discriminate their strategies based on bus shifts, then we have made the hypothesis that probability of a useful contact opportunity between a user and WiFi providers is constant and independent across time slots. Based on this assumption, we modeled and solved the aging control problem, and used trace-driven simulations to show that a very simple threshold strategy derived from our model performs pretty well in practice. Moreover, in a game theoretic framework, we have extended our analysis to multiple users competing for a bonus offered by publishers. In fact, to control the WiFi network load and avoid congestion, publishers can adopt such a policy. We have shown the existence and the uniqueness of a mixed threshold policy. Since the correlations between contact opportunities experienced by a user are always present in real wireless mobile network, we have improved the previous model by using a POMDP rather than an MDP. We derived a sensing policy for the aging control problem, and we have shown several propositions satisfied by optimal policies.

In contrast to what we presented above, where all users communicate with an access point and have, in general, the same channel/environment view, in ad hoc networks, the main difference is the variable topology and the asymmetric view. Indeed, in an ad hoc network, users try to succeed their packets transfer. Based on IEEE 802.11e EDCF standard, we have studied a cross-layered model, and precisely the effect of forwarding on end-to-end performances. We have built a general framework using the perspective of individual senders. Using our model, the attempt and collision probabilities were expressed as a functions of the traffic intensity, topology and routing decision.

7.2 Future guidelines

Our on going works consist in the improvement of our dynamic access control schemes. As the service provider reserves some of its channels to cognitive users by fixing a threshold that must not be exceeded by primary users, the choice of such threshold value is a crucial task. Indeed, decreasing the threshold could produce a high migration rate of SUs to other WSPs and bring down their throughput, while increasing it could degrade the QoS of primary users. This scenario is typically a non-cooperative game

between service providers, where each player try to maximize its profit. More precisely, the problem can be modeled as a stochastic learning game using estimator algorithms such as the pursuit algorithm [103],[104], where each WSP will learn its optimal action in a decentralized fashion.

In ad hoc networks, maintaining connectivity is an important task; mobile terminals should not only spend their battery power to send their own packets, but also for forwarding packets of other mobiles. Since ad hoc networks do not have a centralized base station that coordinates between them, an important and an intuitive question that we have to ask, is to know whether we may indeed expect mobiles to collaborate in such forwarding. Indeed, if mobiles behave selfishly, they might not be interested in spending their precious transmission power in forwarding other mobiles traffic. A natural framework to study this problem is noncooperative game theory. Many possible extensions of this model can be studied, we cite the consideration of a realistic finite storage capacity, the consideration of dynamic environments, in which the network topology and channels change with time, and the non-saturation of users queues.

In chapter 5, we have considered correlations between contact opportunities, and we have shown several propositions satisfied by optimal policies. Now, the objective is to have a complete threshold policy, where a mobile user will choose his action based on the age of its message and the value of its belief. Another direction is considering the interaction between several mobile users in a partially observable environment. Also, we can consider strategic publishers that offer bonus packages to mobile users, so as to motivate them to download updates of a specific or unpopular content.

Appendix A

List of publications

International Journals :

- Mohammed Raiss-El-Fenni, Rachid El-Azouzi, Mohamed El-Kamili, Khalil Ibrahimi and EL Houssine Bouyakhf, "Dynamic Spectrum Allocation with Admission Control based on Cognitive Radio for QoS Support in Multiple Wireless Network", EURASIP Journal on Wireless Communications and Networking 2012 2012:296.
- Rachid El-Azouzi, Essaid Sabir, Mohammed Raiss-el-fenni and Sujit Samanta, "Modelling the Interplay of Cross-layering in IEEE-802.11e-based Multi-hop Ad hoc Networks", submitted to Mathematical Methods of Operations Research journal.

International conferences :

- Mohammed Raiss-el-Fenni, Rachid El-Azouzi, Daniel Menasche and Yuedong Xu, "Optimal Sensing Policies for Smartphones in Hybrid Networks: A POMDP Approach", 6th International Conference on Performance Evaluation Methodologies and Tools, October 9-12, 2012, Cargese, France.
- Rachid El-Azouzi, Daniel Menasche, Yuedong Xu, Mohammed Raiss-el-Fenni and Eitan Altman, "Stochastic Aging Control and Games for Smartphones In Hybrid Networks", submitted to INFOCOM'13.
- Mohammed Raiss-el-Fenni, Rachid El-Azouzi, Andrey garnaev, Elhoussine Bouyakhf, "Optimal Number of Users in Wireless Networks: A Flat Rate Pricing", 8th International Wireless Communications and Mobile Computing Conference, IWCMC 2012, 27-31 August 2012, Cyprus.

- Rachid El-Azouzi, Essaid Sabir, Mohammed Raiss-el-fenni and Sujit Samanta, "Understanding and Analyzing Performances of the IEEE-802.11e in Asymmetric multi-hop Ad hoc Networks", Third International ICST Conference on Ad Hoc Networks Sept. 21-23, 2011, Paris, France.
- Mohammed Raiss-el-Fenni, Rachid El-Azouzi, Mohamed El-Kamili, Khalil Ibrahim and EL Houssine Bouyakhf, "Dynamic Access Control with QoS Levels for Classical and Cognitive Radio Flows", 13-th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, October 17-21, 2010 Bodrum, Turkey.

National conferences :

- Essaid Sabir, Mohammed Raiss-El-Fenni, et Mohamed Elkamili, "Slotted Aloha, Premiere Transmission Différée : Une Nouvelle Solution pour Supporter les Applications Sensibles au Délai", Présenté à la conférence MajecSTIC 2009 Avignon, France, du 16 au 18 novembre 2009.

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