Performance analysis of access control and resource management methods in heterogeneous networks

DIEGO FELIPE PACHECO PARAMO

EDITORIAL
UNIVERSITAT POLITÈCNICA DE VALÈNCIA

Universitat Politècnica de València

Departamento de Comunicaciones

Ph.D. Dissertation

« Performance Analysis of Access Control and Resource Management Methods in Heterogeneous Networks »

Author: Diego Felipe Pacheco Páramo

Advisor: Dr. Vicente Casares Giner
Dr. Vicent Pla Boscà

Valencia
December 2013

Collection doctoral thesis

ISBN: 978-84-9048-191-2 (CD version)

Agradecimientos

Como es de esperarse este trabajo sería imposible de realizar completamente solo, y por lo tanto quisiera expresar mi gratitud a todos aquellos que han sido participes de este. En primer lugar, quisiera agradecer a mis directores de tesis, Vicente y Vicent, por su permanente colaboración, motivación y entusiasmo que no solo mejoraron la calidad de este trabajo sino que me transmitieron el interés permanente por la investigación, y a Jorge, cuya aportación ha sido fundamental para la realización de este trabajo. También al grupo GIRBA, que ha apoyado esta investigación.

Por otro lado, quiero agradecer a aquellos con los que compartí a diario durante la realización de esta tesis: Elena, Maria José, Salva, David, Julián. Todos ellos de alguna manera han contribuido a este trabajo, y han sido una fuente de aliento durante este tiempo.

Asimismo quiero agradecer el apoyo y guía prestados por el Prof. Ian Akyildiz durante mi estancia realizada en el BWN lab. También a los miembros del BWN Lab por su cordialidad y colaboración.

Finalmente, quiero agradecer a mi familia por su generosidad, apoyo permanente y también paciencia. Este trabajo sería impensable sin ellos.

Acknowledgment

As expected, this work is the result of many efforts, and I would like to acknowledge some of them. First of all, I would like to express my gratitude to my advisors, Vicente and Vicent, because their help, motivation and enthusiasm has not only improved the quality of this work but also strengthen my interest in research, and Jorge, whose contribution has been fundamental in the realization of this thesis. To the members of GIRBA.

Also, I would like to thank those who have shared with me every day since I started: Elena, Maria José, Salva, David, Julián. All of them have contributed to this work in one way or another, and have encouraged me through these years.

As well, I want to express my gratitude to Prof. Ian Akyildiz for his hospitality and guidance during my visit to BWN Lab. To the members of BWN Lab for their cordiality and collaboration.

Finally, I would like to thank my family for their generosity, support, and patience.

Abstract

Performance requirements on mobile networks are tighter than ever as a result of the adoption of mobile devices such as smartphones or tablets, and the QoS levels that mobile applications demand for their correct operation. The data traffic volume carried in mobile networks for 2012 is the same as the total internet traffic in 2000, and this exponential growth tendency will continue in years to come. In order to fulfill users' expectations, it is imperative for mobile networks to make the best use of the available resources.

Heterogeneous networks (Hetnets) have the ability to integrate several technologies in a coherent and efficient manner in order to enhance users' experience. The first challenge of heterogeneous networks is to integrate several radio access technologies, which exist as a result of simultaneous technology developments and a paced replacement of legacy technology. A joint management of several RAT's enhances network's efficiency, and this influences user's experience. Another challenge of heterogeneous networks is the improvement of current macrocells through an efficient use of the electromagnetic spectrum. Some approaches aim to optimize the antennas or use higher-order modulation techniques, but a more disruptive approach is the use of dynamic spectrum techniques through a technology known as cognitive radio. Finally, heterogeneous networks should be able to integrate several layers. In addition to the well studied micro and pico cells, a new generation of cheaper and easily configurable small cell networks have been proposed. However, its success is attached to its ability to adapt to the current context of mobile networks.

This thesis aims to analyze three different aspects of heterogeneous networks from a resource management and access control point of view. In the first part, a joint call admission control problem is studied for a network with two radio access technologies and two services. The impact of vertical handoff is studied and the main characteristics of the optimal solutions are described as function of the services and technologies' specifications. In the second part, an analysis over a dynamic spectrum access problem is done in order to establish the effect of fractional guard channels to perform spectrum handovers and to find an optimal value for this parameter. In the final part of this work a signaling load problem over a small cell network is analyzed, and two new schemes for location management are proposed based on a local anchor and the use of direct links among small cells.

Resumen

El escenario actual de las redes móviles se caracteriza por la creciente demanda de los usuarios por los servicios de datos, circunstancia que se ha visto potenciada por la popularidad de los teléfonos inteligentes y el auge de aplicaciones que necesitan de una conexión permanente a internet, como aquellas que hacen uso de recursos en la nube o los servicios de streaming para vídeo. El consumo de datos crece exponencialmente, tanto para los países desarrollados como en los países en desarrollo, y esto ha llevado a los operadores a plantearse soluciones que hagan el mejor uso de las tecnologías disponíbles.

Las redes heterogéneas se caracterizan por utilizar diferentes tecnologías de una manera coherente y organizada para proveer a los usuarios con la calidad de servicio requerida en sus comunicaciones, de tal manera que la comunicación sea para estos transparente. Dicha heterogeneidad se puede dar a nivel de acceso radio, con la coexistencia espacial de tecnologías como 802.11, WiMAX y redes móviles en sus diferentes generaciones, o también a nivel de capas dentro de las redes móviles por medio de macro, micro, pico y femto celdas. A través de un uso organizado de estos múltiples recursos, es posible optimizar las prestaciones de la red y proveer a los usuarios con una mejor calidad de servicio. Otra característica de las redes heterogéneas consiste en la habilidad de hacer un uso eficiente del espectro electromagnético. Junto a las soluciones tradicionales enfocadas en el diseño de antenas o en técnicas de modulación avanzadas, en los últimos años ha ganado terreno la idea de permitir un acceso dinámico al espectro por medio de la tecnología

denominada cognitive radio. Por medio de esta tecnología es posible que un usuario sea capaz de medir el instante en el que una parte del espectro electromagnético no esta siendo utilizado para enviar información, siempre evitando interferir en las comunicaciones de aquellos usuarios que usan dicho espectro regularmente.

En el presente trabajo se analizan tres soluciones en el contexto de las redes heterogéneas desde el punto de vista de la gestión de recursos y del control de acceso. En la primera parte, se estudia un problema de admisión de control conjunto, en el cual se presenta un sistema con dos tecnologías de acceso y dos tipos de servicio. Diferentes políticas son planteadas y un análisis detallado permite plantear el uso eficiente del handover vertical. En la segunda parte se analiza un sistema de acceso dinámico al espectro con el objetivo de estudiar el impacto que los canales fraccionales de reserva tienen sobre la capacidad de realizar handovers espectrales y de esta manera optimizar las prestaciones del sistema. Finalmente, en la última parte del trabajo se plantea un problema de gestión de la localización para una red de small-cells, y se plantean y evalúan dos soluciones para reducir el tráfico asociado a la señalización por medio de un sistema de anclado local y enlaces directos entre las small cells.

Resum

La constat evolució de les xarxes mòbils introdueix requisits cada cop més exigents per a les seves prestacions a causa de l'adopció per part de la societat de dispositius mòbils com smartphones o tablets, i també a causa dels nivells de qualitat de servei que les aplicacions mòbils exigeixen per al seu correcte funcionament. El volum de tràfic de dades suportat per les xarxes mòbils en 2012 es el mateix que el tràfic total en Internet en 2000, i aquesta tendència de creixement exponencial continuarà al llarg dels propers anys. Per a satisfer les expectacions dels usuaris, és imperatiu fer el millor ús possible dels recursos disponibles en les xarxes mòbils.

Les xarxes heterogènies (Hetnets) tenen la habilitat d'integrar diferents tecnologies d'una forma coherent i eficient per a millorar l'experiència dels usuaris. El primer repte de les xarxes heterogènies és la integració de diverses tecnologies d'accés radi (RAT), les quals existeixen com a resultat del desenvolupament simultani de diferents tecnologies i de la substitució gradual de les tecnologies preexistents. Una gestió conjunta de diferents RATs millora la eficiència de les xarxes, tenint açò una gran influència en l'experiència dels usuaris. Un altre repte present en les xarxes heterogènies es la millora de les cèl-lules actuals a través d'un ús eficient de l'espectre electromagnètic. Algunes estratègies tenen com a objectiu l'optimització d'antenes o la utilització de tècniques de modulació d'ordre més elevat, però una estratègia més innovadora és la utilització de tècniques d'espectre dinàmic tals com la tecnologia cognitive radio. Finalment, les xarxes heterogènies deurien ser capaços d'integrar diferents capes. A més de les àmpliament estudiades micro i

pico cells, s'ha proposat una nova generació de small cells, més barates i fàcils de configurar . No obstant, el seu èxit depèn de la seva habilitat d'adaptar-se a l'actual context imposat per les xarxes mòbils.

Aquesta tesis té com a objectiu analitzar tres aspectes diferents relacionats amb les xarxes heterogènies des del punt de vista de la gestió de recursos i el control d'accés. En la primera part s'estudia un problema conjunt de control d'admissió de trucades per a una xarxa que suporta dos tecnologies de accés radi i dos servicis. S'estudia el impacte de traspassos verticals i es descriuen les principals característiques de les solucions òptimes en funció dels serveis i les especificacions tecnològiques. En la segona part es proposa un anàlisis sobre un problema d'accés d'espectre dinàmic per a establir el efecte sobre els canals fractional guard, utilitzats per a dur a terme traspassos espectrals i per a trobar un valor òptim per al paràmetre del canal fractional guard. En la part final d'aquest treball s'analitza un problema de càrrega de senyal en una xarxa small cell, i es proposen dos esquemes nous per a la gestió de localització basats en un punt d'ancoratge local i la utilització d'enllaços directes entre les small cells.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The most demanding challenge that mobile networks face is the continuous growth of data traffic, which according to [Inc13] will increase from 1.6 exabytes (EB) per month in 2013 to 11.2 exabytes per month in 2017. This exponential growth is spurred by users' permanent contact with mobile devices such as smartphones and tablets, and to a lesser but significant extent by the internet of things since M2M communications are expected to represent around 16.5% of total data mobile traffic in 2017. In particular, the massive use of cloud applications with specific Quality of Service (QoS) requirements such as those that include video or music, impose a strong load in mobile networks and leads the growing demands on them.

Heterogeneous networks have the ability to integrate several technologies in an organized and coherent manner to provide users with the best possible connection available in a transparent way. This heterogeneity can be approached by the coexistence of several access technologies such as 802.11, WiMAX and cellular networks, or even by having several layers such as the deployment of macrocells, microcells, picocells and femtocells in mobile networks. By an organized management of these multiple resources, it is possible to optimize network's performance and provide users with the best possible QoS. Network performance can also be enhanced by increasing the efficiency in electromagnetic spectrum use through cognitive radio, a technology that allows users to sense the environment in order to find radio resources to transmit.

With a few decades of history and an enviable level of success, mobile networks have permanently evolved to fulfill the requirements of the epoch. This developments have been grouped into generations, each with different levels of success and, of course, specific technical characteristics. As of 2013, fourth generation (4G) systems are being deployed all over the world, promising a peak speed of 1Gbit/s in contrast to the 28kbit/s reached by first generation (1G) systems. Of course, several changes have been introduced to reach these download capacities in terms of radio access technologies (RAT) or network architecture, for example. Since the introduction of a new technology in mobile networks involves a high cost in terms of time, equipment and even spectral licenses, it is common for different radio access technologies to coexist in order to amortize this investment. On the other hand, the success of WLAN must be acknowledged, since currently most mobile terminals include this type of RAT, and an important part of traffic is served through this type of networks. Therefore, it becomes a necessity to integrate the management of the available radio access technologies to efficiently exploit them and hence, provide a better service to users. In the context of a multi-RAT environment, common radio resource management (CRRM) has been proposed as a model that groups a set of functions that control the use of radio resource units (RRUs) of several RATs to provide users with the best possible connection since, as it is shown in [THH02], this integration enhances the overall performance. Some of the functions that CRRM includes are Packet Scheduling (PS), Congestion Control (CC), Handover Control (HC) and Admission Control (AC). In this work we are particularly interested in joint call admission control (JCAC) and joint handover control (JHC) functions, where joint makes reference to the ability to consider all the available RATs in the function. JCAC is responsible for choosing the appropriate RAT for each arriving call according to user's requirements and network's objectives. Therefore, this decision can be influenced by both parties, with several grades of participation. JHC is another important feature of CRRM, since it allows vertical handover (VH). This function allows an ongoing call to be served by a different RAT and therefore is analogous to traditional horizontal handover, based on mobility. A rearrangement of resources through VH enhances network's performance, and allows users to dynamically adapt to changing network's conditions. In this work, we study the influence of VH to optimize the performance of a multiservice system.

Although geographical reuse of frequencies has been highly successful as the keystone of cellular networks in a scenario where licensed spectrum assignment is fixed, several measurements have proven that spectrum usage is very inefficient, showing average utilization values as low as 5% in Chicago, 20% in New York [Com05], and 13% in Dublin [Com07]. These figures are very important since spectrum is the most important resource of mobile communications and its inefficient use is detrimental to the performance of the whole network. To overcome this deficiency, Cognitive Radio (CR) has been proposed as a technology that allows to share the licensed spectrum with CR users. This sharing is done opportunistically, since CR users would access the spectrum without interfering with licensed spectrum users. This new paradigm raises several new challenges in order to be feasible, and some of them have been active research topics in the last few years. Some of them are the capacity of CR users to detect those parts of the spectrum that are available to transmit, choose among the possible candidates and finally be able to release this spectrum as soon as a licensed spectrum user wants to use it. Of course, this access has to be done in cooperation with other CR users, which makes decisions more complex. An important function that arises in CR scenarios is the ability of CR users to switch the selected spectrum when it is needed by a licensed spectrum user. This function has been defined as spectrum handover, analogously to the horizontal and vertical handoff mentioned earlier. In this work, we study the effects of guard channels for spectrum handover in CR systems, and how its adjustment can optimize its performance.

Multi-layer mobile networks have been traditionally used to overcome the capacity shortage in dense metropolitan areas by the use of small coverage directed antennas. These type of cells, such as microcells, picocells, etc, have the same characteristics as metropolitan macrocells, and require the same considerations for deployment. On the other hand, a new generation of small cells (SC) with reduced coverage areas have been proposed to overcome the increase of indoor data traffic requirements. These small cells are envisioned as low power, reduced area coverage cells that use the licensed spectrum and an IP-Based backhaul that will typically have a lower bandwidth than that of microcells. In [Lab12], it is stated that up to 70% of data traffic occurs indoors and since data traffic grows exponentially as mentioned earlier, telcos have foreseen the need to offload indoor traffic to this type of cells, reducing deployment costs considerably [ff10]. As expected, large deployments of small cells introduce new challenges [CAG08] [ACD+12] given its backhaul limitations and coexistence with other layers of mobile networks. The most studied subject in SCs is interference. Since these cells use the same licensed spectrum as macrocells, users located near the SC coverage area but who are being served by the macrocell may be interfered in the downlink by the SC since it is closer. Usually this could be solved by connecting the user to the SC, but this may not be possible since some of them only allow subscribed users (SC in closed or hybrid mode). On the other hand, other coordination methods to reduce interference may not be suitable since the delays associated with the backhaul of the small cell are too high. This issue is particularly problematic for mobility, since it reduces the ability to perform a successful handover between SCs and macrocells or even between SCs. Successful handovers require some degree of communication between the involved cells, but also between them and the core network. Since this link is seriously limited not only by the capacity (xDSL is permitted) but also by latency, it is difficult to guarantee that all the required signaling occurs on time. Additionally, since the coverage areas are smaller a higher number of handovers are expected and this increases the processing cost in the core network. The same issues arise for mobility management in idle-mode i.e. location management. Large deployments of small cells can increase the capacity of heavily dense metropolitan areas, but also increase the coverage where no macrocells exist. This means that Location Updates (LUs) and paging procedures have to be performed at a small cell layer, which increases the load on the core network and reduces the capacity of the backhaul, while latency issues remain. In this work we are interested in location management schemes for small cell networks, and we propose some solutions that are compared with a standard solution.

This thesis aims to contribute to the analysis of resource management and access control methods in heterogeneous networks by evaluating three different aspects: resource management in multiple RATs, access control in spectrum sharing and signaling overhead in multiple layers. The work is structured in 5 chapters, where the first is the introduction. Chapter 2 studies a resource management problem for a system with two RATs and two types of service. An MDP is proposed to find an optimal policy using VH, and a modified solution is proposed to reduce the computational cost. Next, in Chapter 3, we analyze the influence of both integer and fractional guard channel in a spectrum sharing problem. This analysis is used to optimize system's performance. In Chapter 4 , we study a resource management problem for a small cells network, in order to reduce the signaling overhead associated to location management. Finally, in Chapter 5 a summary of the main contributions of this thesis are presented. Also, a sketch of possible future contributions are highlighted.

Chapter 2

Radio resource management in multiaccess networks

Wireless networks have the urge to integrate all the available radio access technologies (RATs) in order to efficiently exploit the advantages that all of them have to offer. This heterogeneous scenario is the product of the success of parallel developments such as 802.11, WiMAX and mobile networks, but also of the gradual upgrading of cellular networks technology. The exploitation of all the available RATs in the same geographical area allows the subscribers to achieve a permanent connection with the best possible performance [WS07].

Common radio resource management (CRRM) has been proposed as a model to control several RATs in a coordinated way, exploiting the fact that this coordination allows an improvement in the use of the limited resources [THH02]. The available functions of CRRM are Joint Call Admission Control (JCAC), Joint Congestion Control (JCC), Joint Handover Control (JHC), Joint Packet Scheduling (JPS) and Joint Power Management (JPM). In the case of JCAC, in this new scenario it not only defines if a session should be accepted or not, but also in what technology [FC08]. Once a call has been accepted, it can be served by a different RAT using JHC.

Some JCAC proposals in heterogeneous networks, such as those found in [PDJMT04][SCD06], were designed to achieve a certain degree of load balancing among the different access networks, which translates into a better resource utilization. More specifically, in [SCD06] several JCAC policies have been studied for a scenario similar to ours and their performance measured in terms of throughput and blocking probability. However, while in [SCD06] only simple heuristic policies are considered, we follow an optimization approach.

In [YK04] a Markov model is used for an heterogeneous network (WLAN and CDMA), and linear programming is used to solve the optimization problem. This study explicitly acknowledges the inherent complexity of the problem which could make it computationally intractable for large systems. This fact leads the authors to propose reinforcement learning as a possible solution method. Our study differs from the one in [YK04] in that our main objective is the characterization of the optimal policies and the design of heuristic policies. In [KCH04] they formulate an optimization problem as a Markov decision process and solve it using genetic algorithms. However, the objective of their study is different from ours, and therefore the optimization functions depend on different parameters.

Finally, fuzzy-based solutions are used in [ASPRG04][FC06]. These solutions take different user and system parameters, weight them, and produce an online decision. On the other hand, our interest is to find optimal solutions, characterize them and synthesize heuristic solutions that can minimize the blocking probabilities, or bound them, and maximize the throughput.

The work in this chapter is in part motivated by the study in [GPRSA08], where a scenario for two radio access technologies and two services is analyzed for three different solutions. The main difference in this work is that we follow an optimization approach, where the main characteristics of the optimal solutions are obtained to define heuristics that outperform the three original solutions proposed. Another important difference is that we consider vertical handoff which has an important impact in the optimal solutions presented.

In this chapter we focus on two functions of CRRM, JCAC and JHC for a system where two services are provided. In the first part, we apply an optimization approach for the JCAC problem as a Markov decision process (MDP), and the optimal policies found are analyzed to define heuristics. These heuristics are very simple and overcome the problem of the computational cost associated to obtaining the optimal policies. Heuristic policies are used to define the VH types that enhance system's performance. This approach is different to that used in [SNW06][GS08] where VH was used to privilege user's preferences. These VH types are used to define new optimal policies and through a detailed analysis new heuristics with VH are described and compared to other solutions. Also, we evaluate for the ranges of costs for which VH is advisable. Some analysis of VH cost has been done in [HNH05], where a monetary cost was associated. However, we consider that our approach is more general. Finally, an approximated method to reduce the computational cost of finding the optimal policy is described, and its appropriateness is checked. The content of this chapter has been published in [DVVJ11][DVVJ12][DJVE13].

The rest of the chapter is organized as follows. In Section 2.1, we describe the Markov model for the system with two RATs and two services, and define the performance parameters. In Section 2.2 the solution for a JCAC problem is found through dynamic programming. In Section 2.3, we perform the analysis of the same system including JHC, which enhances the overall performance. In Section 2.4, we define an approximated method that reduces the computational cost of dynamic programming achieving a similar performance. Final remarks are done in Section 2.5

2.1 System model and optimization problem

We study a system with two wireless access networks that use two multiple access techniques: TDMA and WCDMA. Their characteristics allow us to model technologies such as GSM and UMTS. However, the proposed model and analysis can be extended to other multiple access techniques like OFDMA, which has been defined to support, for example, WiMAX and LTE. Additionally, both access networks provide voice and data services in the same area, as it was proposed in [GPRSA08]. When a session arrives, a decision has to be made on whether it should be accepted or not, and also in what technology should be served. Initially, we consider that a decision is made once a session starts and will be held until it terminates, i.e. there are no vertical handoffs.

In order to obtain an analytically tractable model, we assume that voice (data) session arrivals follow a Poisson process with rate $\lambda_v(\lambda_d)$. We also assume that the service time for voice sessions is exponentially distributed with mean $1/\mu_v$. On the other hand, as data sessions generate elastic traffic, their sojourn time will depend on the available resources. The size of the flows generated by the data sessions is exponentially distributed with mean σ (in bits). If BRd is the data bit rate experienced for a given user, then the service time will be exponentially distributed with mean $1/\mu_d = \sigma/BR_d$. Clearly, BR_d might depend on the system state as discussed later.

2.1.1 State space

The system is modeled as a 4 dimensional continuous time Markov chain (CTMC), with states represented by the vector $\boldsymbol{s} = (s_1, s_2, s_3, s_4)$ where s_1 represents the number of ongoing voice sessions on TDMA, s_2 the data sessions on TDMA, s_3 the voice sessions on WCDMA and s_4 the data sessions on WCDMA. We define C as the fixed number of channels in TDMA. A voice session will always use a whole channel, so there can only be C simultaneous voice sessions on this technology. On the other hand, data sessions can share a channel when TDMA is at full capacity, in such a way that n_c data sessions can be served per channel. This means that a maximum of $C \cdot n_c$ simultaneous data sessions can be active in TDMA. According to this, the first condition that a state must fulfill to be feasible is given by

$$s_1 \cdot n_c + s_2 \leq C \cdot n_c. \tag{2.1}$$

The capacity on WCDMA is defined by

$$s_3 \cdot V + s_4 \cdot D \leq \eta_{ul}, \tag{2.2}$$

where $V=\left(\frac{W/BR_{w,v}}{(E_b/N_0)_v}+1\right)^{-1}$, $D=\left(\frac{W/BR_{w,d}}{(E_b/N_0)_d}+1\right)^{-1}$, W is the chip rate, $BR_{w,x}$ is the bit rate used for transmitting service x in WCDMA, $(E_b/N_0)_x$ is the bit energy to noise density required for service x, and η_{ul} is the uplink cell load factor. This is the same expression used in [GJP+91]. Considering that each technology has independent resources, the feasible combination of data and voice users can be determined for each technology separately. We define S as the set of feasible states, that is all the state vectors s that fulfill the conditions defined in (2.1) and (2.2). OFDMA-based systems commonly operate as FDMA-TDMA systems, where the resources to be shared are organized as a two-dimensional matrix of sub-channels and time-slots that repeats every frame (e.g., every 5 ms in WiMAX) [KR02], [BSKD06]. In addition, the same resources (sub-channels and time-slots) can be shared by different sessions in consecutive frames. Although the support of preambles imposes some difficulties to share the resource efficiently, effective algorithms have been proposed to solve this problem [BSKD06]. Then, the admission control problem in OFDMA-based systems can be formulated as in (2.1), where each accepted session of each service category consumes a certain constant amount of resources in the two-dimensional resource matrix [PMBCG08], [PS11].

2.1.2 System metrics

Different performance parameters can be determined, once the steady state probabilities of the CTMC have been obtained. In particular, we are interested in the voice blocking probability, the data blocking probability, and the total throughput. The blocking probability refers to the fraction of sessions initiation requests that are blocked. To calculate the throughput we have to consider that the bitrate is independent for each service and technology and that data sessions in TDMA can share a channel, which is reflected in the min $(C - s_1, s_2)$ factor of the following equation:

$$Th = \sum_{s \in S} \Pi(\boldsymbol{s}) \big(s_1 BR_{t,v} + s_3 BR_{w,v} + \min(C - s_1, s_2) BR_{t,d} + s_4 BR_{w,d} \big), \quad (2.3)$$

where $\Pi(s)$ is the steady state probability of being in state s and $BR_{x,y}$ is the bit rate used for transmitting service y (voice or data) in technology x (TDMA or WCDMA).

2.1.3 Optimization problem

Voice and data arrivals can occur at any state of the CTMC defined in the last section. Then, at each state, a decision must be made on whether an arriving session should be admitted and the appropriate technology. In a Markov decision process (MDP), a policy Ψ defines which actions a=(a_s^v,a_s^d) should be taken at each state $\boldsymbol{s}$ when voice (a_s^v) or data (a_s^d) arrivals occur. It should be clear that decision epochs occur only at arrivals. The main objective is to find among the possible policies the one that optimizes a chosen function. In this system, the set of actions A defines the possible values for a_s^v and a_s^d, and it is defined in Table 2.1.3. Fig. 2.1 shows the transitions from state $\boldsymbol{s}$ for arrivals. These transitions are clearly conditioned by a_s^v and a_s^d, where e_i is a 4 dimensional vector of zeros with a 1 on the i–th position. The transitions from state $\boldsymbol{s}$ for departures are shown in Fig. 2.2.

We define now three different admission schemes and set the values taken by a_s^x accordingly, where x could be voice or data. These policies were suggested and analyzed in [GPRSA08]. Let AC_{TDMA} and AC_{WCDMA} be the available free capacity in TDMA and WCDMA, respectively.

value	*action*
0	Block call
1	Send call to TDMA
2	Send call to WCDMA

Table 2.1: Set of possible actions A

Scheme *i* : sessions are sent to TDMA (if possible)

$$a_s^x = \begin{cases} 1 & \text{if } AC_{TDMA} > 0 \\ 2 & \text{if } AC_{TDMA} = 0 \text{ and } AC_{WCDMA} > 0 \\ 0 & \text{if } AC_{TDMA} = AC_{WCDMA} = 0 \end{cases}$$

Scheme *ii*: sessions are sent to WCDMA (if possible)

$$a_s^x = \begin{cases} 2 & \text{if } AC_{WCDMA} > 0 \\ 1 & \text{if } AC_{WCDMA} = 0 \text{ and } AC_{TDMA} > 0 \\ 0 & \text{if } AC_{TDMA} = AC_{WCDMA} = 0 \end{cases}$$

Scheme *iii*: sessions are sent to the technology with lower occupation

$$a_s^x = \begin{cases} 1 & \text{if } AC_{TDMA} > AC_{WCDMA} \\ 2 & \text{if } AC_{WCDMA} > AC_{TDMA} \\ \text{random} & \text{if } AC_{WCDMA} = AC_{TDMA} > 0 \\ 0 & \text{if } AC_{WCDMA} = AC_{TDMA} = 0 \end{cases}$$

Using these schemes we define three policies:

Policy	Scheme for voice	Scheme for data
1	*i*	*ii*
2	*ii*	*i*
3	*iii*	*iii*

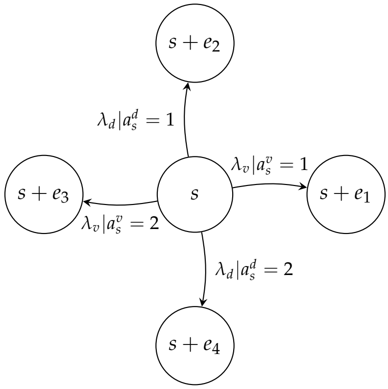


Figure 2.1: Transitions for voice and data arrivals.

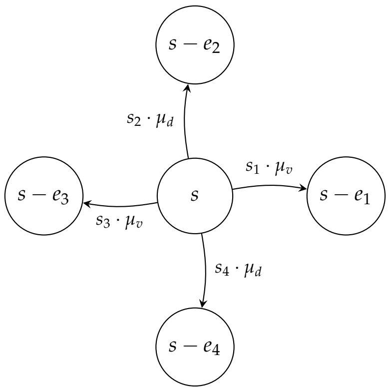


Figure 2.2: Transitions for voice and data departures.

It should be noted that Policies #1 and #2 exploit the hypothesis that each technology is more appropriate for a specific service, which is not the case of Policy #3 that focuses on improving radio resource utilization.

The state space of the MDP is defined by (2.1) and (2.2), and the possible set of actions and the transition rates associated to them are defined in Table 4.1 and Figs. 2.1 and 2.2. Since our interest relies on data and voice blocking probabilities, as well as the total throughput, we have defined two different objective functions. The first one, is the weighted sum of the voice and data blocking probabilities (BP_v and BP_d),

$$F_{BP} = BP_v \cdot \alpha + BP_d \cdot (1 - \alpha). \tag{2.4}$$

The parameter α, $0 \leq \alpha \leq 1$, is the one responsible for giving more or less weight to each blocking probability. When α is closer to 0, minimizing the objective function will have a bigger impact on data blocking probability than on voice blocking probability, and the opposite will happen when α is closer to 1. Thus, α relates the way in which the blocking probabilities will be minimized. The cost function associated to the objective function for each feasible state $\boldsymbol{s}$ is

$$\mathrm{cost}(\boldsymbol{s}) = 1 - (\alpha \cdot F_v(a_s) + (1 - \alpha) \cdot F_d(a_s)), \tag{2.5}$$

where $F_x(a_s)$=1 if a_s is 1 or 2, and 0 otherwise, being x the service.

The second objective function is the aggregated throughput, so in that case we try to maximize the value defined by (2.3). The reward for each state $\boldsymbol{s}$ is

$$\mathrm{cost}(\boldsymbol{s}) = s_1 BR_{t,v} + s_3 BR_{w,v} + \min(C - s_1, s_2) BR_{t,d} + s_4 BR_{w,d}. \tag{2.6}$$

Therefore, the reward associated to each state when maximizing the throughput does not depend on the actions taken on that state. It must be noted that we use the term cost for notational purposes, even when a reward is expected from throughput.

Table 2.2: Initial Scenario for Policy Iteration.

WCDMA	TDMA
W=3.84 Mcps	C = 4
$(E_b/N_0)_v$=14 dB	n_c= 2
$(E_b/N_0)_d$=14 dB	$BR_{t,v}$=12.2 kbps
$BR_{w,v}$=12.2 kbps	$BR_{t,d}$=44.8 kbps
$BR_{w,d}$=44.8 kbps	
η_{ul}= 1	

Clients
λ_v= 0.025
λ_d= 0.134
μ_v= 0.0083
σ= 1 Mb

2.2 Joint radio resource management in multiaccess networks

2.2.1 Optimal policy analysis: static scenario

The parameters of the system are defined in Table 2.2. As it can be seen, bit rates are independent of the technology used, and are higher for data than for voice. Also, the $((E_b/N_0)$ required for both services in WCDMA are the same. The maximum voice and data capacities are of 4 and 8 users in TDMA and of 13 and 4 users in WCDMA. The system parameter values have been chosen in order to maintain a similar capacity on both technologies and to keep the optimization problem computationally tractable. The objective of this section is to explore the optimal policy when the two optimization functions are used: blocking probability and throughput.

Blocking function optimization

Unless otherwise stated, throughout the document we use a value of $\alpha = 0.5$. That is, the objective function will be defined by $F_{BP}(\pi)$=$0.5 \cdot BP_v$+ $0.5 \cdot BP_d$. Fig. 2.3 shows the value of the objective function for every iteration until the optimal policy is achieved and results are compared with those obtained with the fixed policies described in Section 2.1.3. We can summarize the main characteristics of the optimal policy as follows:

Service	*Action*
Voice	scheme *ii*
Data	• if there is no channel sharing on TDMA: scheme *i* • if there is channel sharing on TDMA: $\cong$ scheme *iii*

The initial policy, Policy #2, has the closest performance to the optimal policy because they both send voice sessions to WCDMA (scheme *ii*). The decisions for data sessions depend on channel sharing since this reduces the transmission rate, which raises the residence time and thus the blocking probability. Therefore, channel sharing produces a policy very similar to scheme *iii* where resources are used according to occupation.

Only 22.3% of a_s^d from Policy #2 differ from the optimal, and there is only a 6.1% probability for these actions to occur. However, results differ considerably. The cost for the optimal policy is 34.78% of the one obtained with Policy #2, and of course similar results are found on BP_v and BP_d, as it is shown in Figs. 2.4(a) and 2.4(b). This improvement also added 462 *bps* to the throughput obtained with Policy #2.

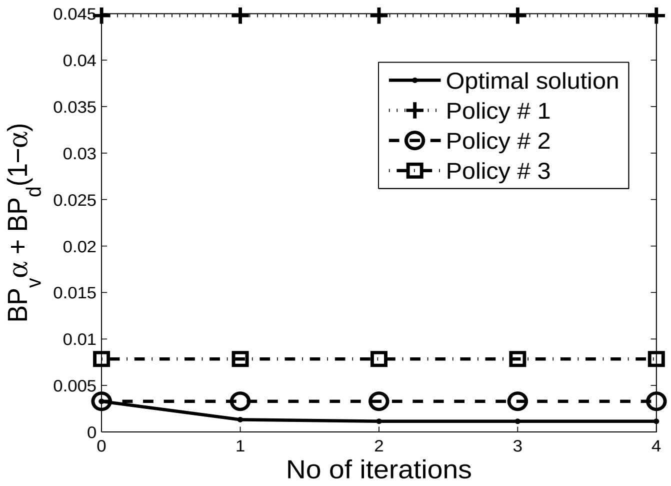


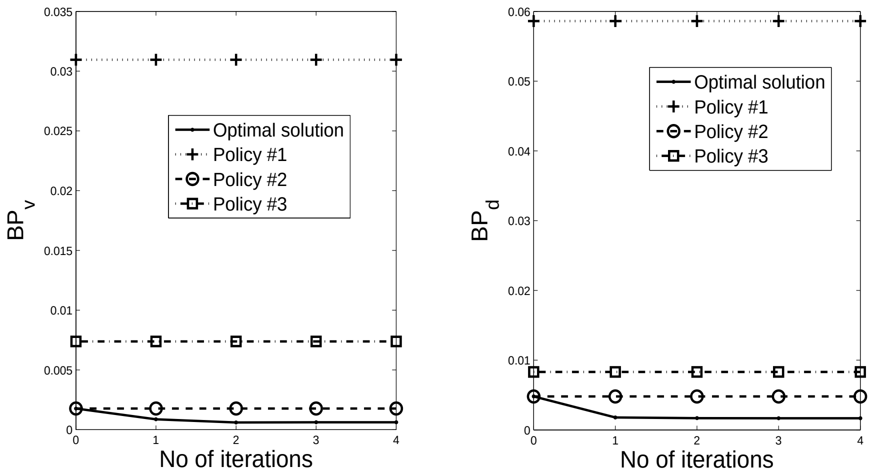
Figure 2.3: Blocking probability function optimization.

Throughput optimization

The characteristics of the optimal policy for throughput optimization, can be summarized as:

Service	*Action*
Voice	scheme *ii* with blocking
Data	• if there is no channel sharing on TDMA: scheme *i* • if there is channel sharing on TDMA: $\cong$ scheme *iii*

Although voice sessions are sent to WCDMA (scheme *ii*), there may be blocking when there is available capacity on TDMA. This happens in order to save capacity for data calls, which contribute more to the total throughput. In the



(a) *VoiceBlockingProbability*.

(b) *DataBlockingProbability*.

Figure 2.4: Blocking Probabilities.

optimal policy, nearly 25 % of the states where no more capacity is available on WCDMA, even if there is capacity in TDMA, voice calls are blocked. Also, since channel sharing on TDMA directly reduces the total throughput, a policy similar to scheme *iii* is used for data sessions.

Figure 2.5 shows the throughput until the optimal policy is reached. After two iterations, the throughput raises to 170.366 *kbps*, a gain of 474 *bps* over Policy #2. The policy obtained with the first iteration is very similar to the optimal, since the second iteration only improves the total throughput in 35.8 *bps*, about 8% of the 438.9 *bps* gained before. An interesting fact of throughput optimization, is that it also improves BP_v and BP_d. Since these parameters have very low values in the initial policy the improvement is small, going from 0.17 % to 0.079 % for BP_v and from 0.48 % to 0.15 % for BP_d, but it shows their correlation with the total throughput. Actually, the BP_d is lower than the one obtained optimizing the blocking function (0.167 %),

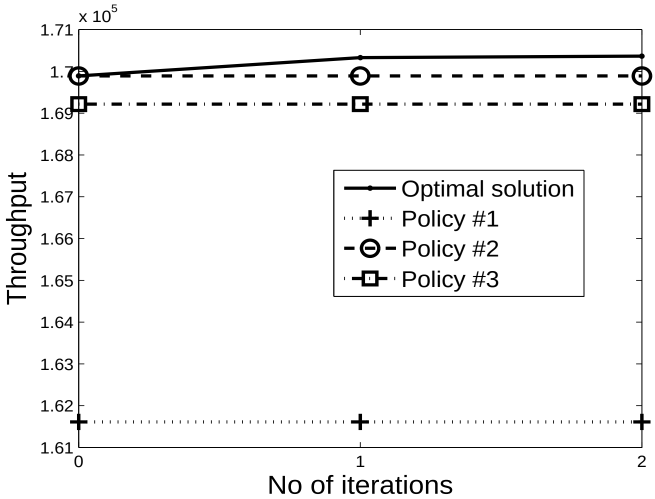


Figure 2.5: Throughput optimization.

indicating the importance of accepting data calls for the improvement of the total throughput.

2.2.2 Optimal policy analysis: parameter variation

In this part we study the impact of traffic values over the optimal policy and compare it with the one obtained by the heuristic policies defined in Section 2.1.3, which were proposed previously in the literature. We also characterize the optimal policies obtained for each load point, and based on their dynamic behavior, we define a heuristic policy.

Voice users arrival rate variation

Although they are not identical, the main characteristics of optimal policies for both optimization functions as λ_v grows can be summarized as:

Service	*Lower* λ_v	*Higher* λ_v
Voice	scheme *ii*	scheme *ii* with blocking
Data	If there is no channel sharing on TDMA: scheme *i*	If there is no channel sharing on TDMA: scheme *i*
	if there is channel sharing on TDMA: $\cong$ scheme *iii*	if there is channel sharing on TDMA: $\cong$ scheme *iii*, preferably TDMA

Figure 2.6 shows the results obtained with the optimal policy for the blocking optimization function, and the values obtained with the fixed policies. When λ_v reaches 0.047, the offered load for voice is 5.64 Erl, almost two times the offered load for data (3 Erl). Given the great impact on data calls, the optimal policy blocks voice calls, and this is more intense for higher values of λ_v. For λ_v=0.047 only 3 of 80 states where voice calls were sent to TDMA according to scheme *ii*, decide to block in the optimal policy. At this point, BP_v=0.2 % and BP_d=1 %. When λ_v grows to 0.065, 26 of those 80 states block voice calls, that is eight times more states than before. As expected, BP_d only grows to 2.5 %, but the impact on BP_v is bigger, since it grows almost ten times, to 2.056 %.

Dependance on channel sharing for a_s^d is maintained for all λ_v, but once sharing is mandatory, some changes occur. As λ_v grows, the number of states that decide to send data calls to TDMA under this circumstances, grows from 180 of 400 when λ_v=0.005 to 225 of 400 when λ_v=0.065. This is done in order to reduce BP_v, since WCDMA capacity is saved for voice calls. It is also worth noting that when TDMA is almost at full capacity (>95%), data calls are blocked. This effect can be seen for the full range of λ_v values that appear on Fig. 2.6.

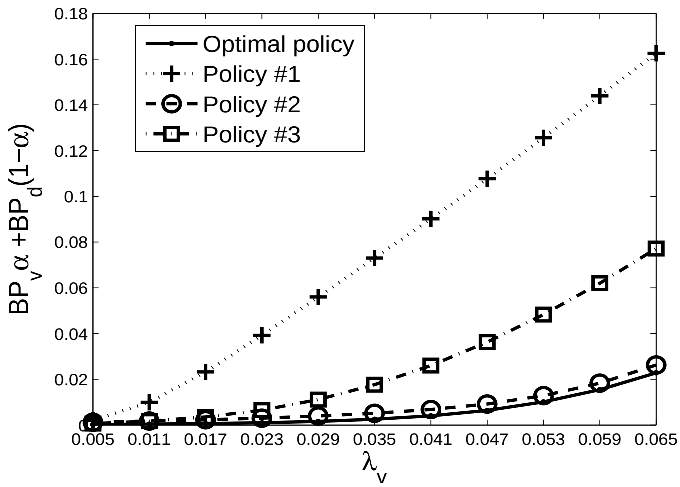


Figure 2.6: Blocking function for various λ_v.

Figure 2.7 shows the throughput when it is used as the optimization function for the optimal policy and the three fixed policies as λ_v grows. As λ_v grows, it becomes mandatory to save resources for data calls since they have a higher throughput. For this reason, voice calls may be blocked even when there is room on TDMA. For λ_v=0.005, 14 of 80 states where occupancy on WCDMA is full but there is still room on TDMA, block voice calls. When λ_v grows to 0.065, 36 of the same 80 states block voice calls. This affects BP_v, and when λ_v>0.041, the optimal policy has a higher BP_v than Policy #2.

Dependance on channel sharing for a_s^d is maintained for all λ_v, but when sharing is mandatory, optimal policies vary. As λ_v grows, the occupation of WCDMA does too, so more data calls must be sent to TDMA in order to increase the total throughput. When λ_v=0.005, 144 of the 400 states that use TDMA channel sharing send data calls to TDMA. For λ_v=0.065, 212 of the same 400 states send calls to TDMA.

Therefore, for both optimization criteria, voice calls are sent to WCDMA, with more blocking states as λ_v grows, and data calls are sent to TDMA while

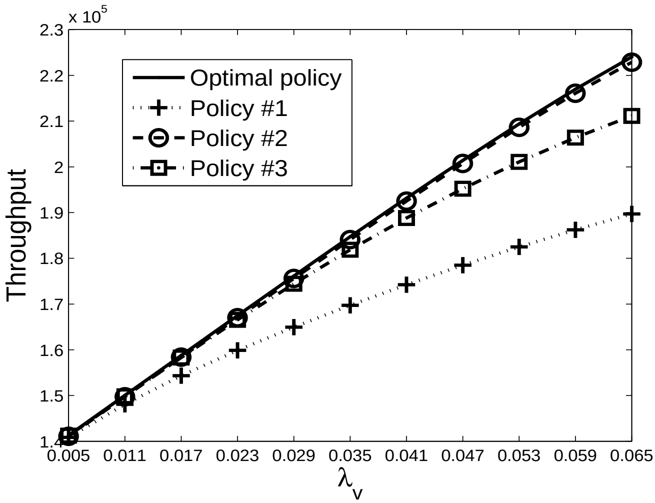


Figure 2.7: Throughput for various λ_v.

no sharing is needed. When sharing is mandatory, data calls may be sent to WCDMA or TDMA with more states using TDMA as λ_v grows.

Data users arrival rate variation.

Although not identical, the main characteristics of the optimal policies for both optimization function as λ_d grows can be summarized as:

Service	*Lower* λ_d	*Higher* λ_d
Voice	scheme *ii*	scheme *ii*
Data	If there is no channel sharing on TDMA: scheme *i*	If there is no channel sharing on TDMA: scheme *i*
	if there is channel sharing on TDMA: $\cong$ scheme *iii*	if there is channel sharing on TDMA: $\cong$ scheme *iii*, preferably WCDMA

Figure 2.8 compares the blocking function values for the optimal policy with different values of λ_d with those obtained with the three fixed policies. In this scenario, voice calls follow scheme *ii* for every λ_d, showing that the load of data calls has no impact on a_s^v. On the other hand, the big influence of TDMA occupancy over a_s^d, suggest the opposite. In fact, when λ_d=0.2, data calls arrive with a higher rate than voice calls, so in order to maintain a low objective function value, it is necessary to send more data calls to WCDMA so TDMA's capacity is not exhausted too fast. This is the opposite case of the one we saw in the last section where as λ_v grew, more data calls were sent to TDMA. The second effect is that as λ_d grows, it is necessary to block calls in order to minimize the optimizing function. For the values of Fig. 2.8, the system has 1000 states. Only 70 of the total do not allow data calls, thus these are data blocking states. For the optimal policy, while $\lambda_d \leq 0.095$, data calls are only blocked on those 70 states. Once this value is surpassed, the optimal policy may block data calls even when there is capacity left. When λ_d=0.11, 4 of the 930 states with capacity left decide to block data calls, and this number grows to 30 of those 930 states when λ_d=0.2, more than seven times the initial number of blocking states.

Figure 2.9 shows the throughput when it is used as the optimization function for various λ_d. Since data calls have a higher throughput, the opti-

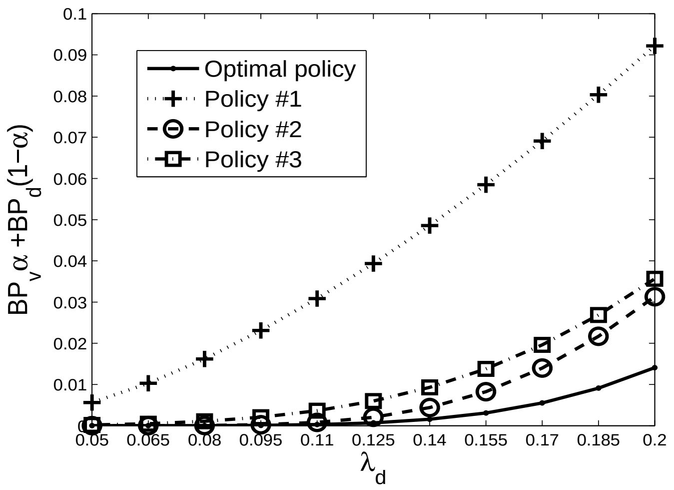


Figure 2.8: Blocking function for various λ_d.

mal policy may penalize some voice calls to maximize the objective function. When λ_d=0.2, BP_v is higher in the optimal policy than in Policy #2, reaching 2%. In fact, if we let λ_d=0.275, BP_v for the optimal policy would be higher than any of the fixed policies. In order to maximize the throughput, the opposite happens for BP_d, which is always the lowest in the optimal policy. As usual, voice calls are treated according to scheme *ii*, but as λ_d grows higher than 0.05, instead of sending calls to TDMA when WCDMA is full, they may be blocked. The number of states doing this grows slowly, but when λ_d=0.3 no voice calls are ever sent to TDMA, saving the space for data calls.

TDMA occupancy influence on a_s^d is increased by λ_d. When sharing becomes mandatory, as λ_d grows there seems to be a preference for sending calls to WCDMA using the capacity saved by voice calls. As a consequence of the importance of data calls for throughput, for the values of λ_d in Fig.2.9, the optimal policy never blocks data calls unless there is no other chance. That is, as λ_d grows voice calls are always sent to WCDMA, but some blocking may appear when we optimize the throughput. On the other hand λ_d does

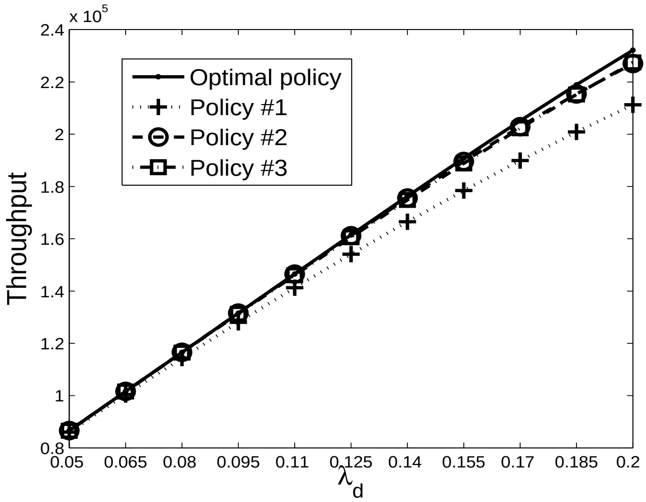


Figure 2.9: Throughput for various λ_d.

not affect decisions for voice calls when the blocking function is optimized. Data calls are sent to TDMA while no sharing is needed, but when sharing is mandatory, calls may be sent to TDMA or WCDMA, but as λ_d grows, a clear tendency towards WCDMA is seen for both optimization criteria.

Voice users service rate variation

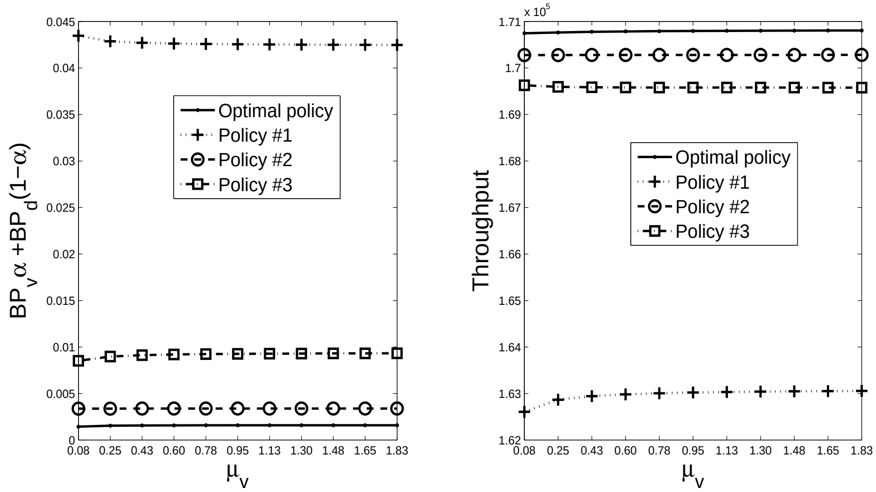
Figure 2.10(a) shows the blocking function value while maintaining a constant offered traffic of 3 *Erl* for both services (as the static scenario), and changing μ_v from 0.0833 to 1.833. It is easy to realize how changes on μ_v have little or no impact in the blocking function for different policies. This behavior is a result of what happens with the blocking probabilities and the throughput, where the results are almost constant for the full range of μ_v. The optimal policies can be summarized as:

Service	*Lower* μ_v	*Higher* μ_v
Voice	scheme *ii*	scheme *ii* with blocking
Data	If there is no channel sharing on TDMA: scheme *i*	If there is no channel sharing on TDMA: scheme *i*
	if there is channel sharing on TDMA: $\cong$ scheme *iii*	if there is channel sharing on TDMA: $\cong$ scheme *iii*.

As μ_v grows, some voice calls are blocked. However, it only differs on 0.2% of the states when μ_v changes from 0.258 to 1.833. Also, μ_v has little influence over a_s^d. As μ_v grows, a small percentage of states (<5%) where calls used to be sent to WCDMA are sent to TDMA. In Fig.2.10(b) it is shown the throughput as the optimizing function for a constant load of 3 *Erl* in both services, while μ_v changes. When throughput is optimized, BP_v can be higher in the optimal policy than in other policies. The main characteristics of the optimal policies can be summarized in the same way as in the blocking function optimization shown before in this section.

Data service rate variation

Fig.2.11(a) shows the blocking function value for a constant load of 3 *Erl* on both services while μ_d changes. To change this parameter, we kept $BR_{x,d}$ in 44.8 kbps, and changed the mean data length σ. The main characteristics of the optimal policies can be summarized as:

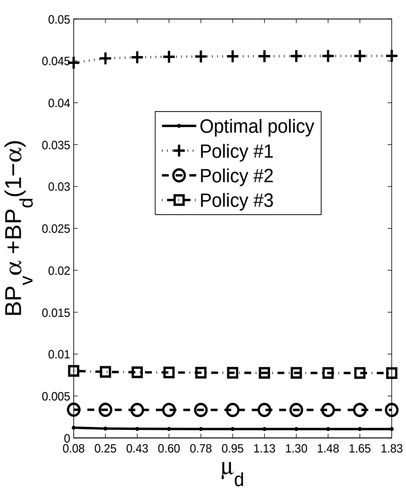


(a) *Blocking Optimization.* (b) *Throughput Optimization.*

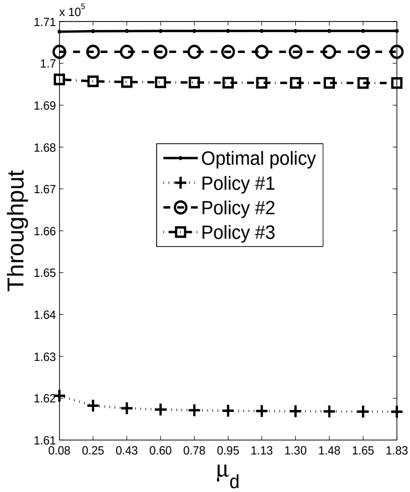
Figure 2.10: Optimization for various μ_v.

Service	*Lower* μ_d	*Higher* μ_d
Voice	scheme *ii*	scheme *ii* with blocking
Data	If there is no channel sharing on TDMA: scheme *i*	If there is no channel sharing on TDMA: scheme *i*
	if there is channel sharing on TDMA: $\cong$ scheme *iii*	if there is channel sharing on TDMA: $\cong$ scheme *iii*.

In Fig.2.11(b) appears the throughput (used as the optimization function) for the optimal and the fixed policies when μ_d changes and the load for each



(a) *Blocking Optimization.*



(b) *Throughput Optimization.*

Figure 2.11: Optimization for various μ_d.

service is kept constant (3 *Erl*). The optimal policies are very similar to those obtained with the blocking function. For the lowest values of μ_d in Fig.2.11(b) most of the states where the capacity of WCDMA is full, decide to block calls even when there is space left on TDMA. As μ_d grows, these states decide to send voice calls to TDMA. This blocking is done in order to protect data calls, whose contribution to throughput is higher.

2.2.3 Heuristic policy

According to the analysis realized in previous sections, it is possible to define a heuristic policy based on those characteristics that were common for all the scenarios. Therefore, the heuristic policy is summarized as:

Service	*action*
Voice	scheme *ii*
Data	• if no channel sharing on TDMA: scheme *i* • if channel sharing on TDMA: scheme *iii*

The heuristic policy sends voice calls to WCDMA which is a very simple solution that is consistent with optimal solutions of Section 2.2.2 and for the lower values of λ_v in Section 2.2.2. On the other hand, the optimal solution for data calls is more complex and composed by two stages as previous analysis showed. On the first stage, data calls are sent to TDMA (scheme 1) until the arrival of a new call would force channel sharing. On the second stage decisions depend on voice and data loads, as can be seen from Sections 2.2.2 and 2.2.2. When λ_v grows, data calls are sent to TDMA, making the optimal policy for data calls as scheme 1. On the other hand, when λ_d is the one that grows, more data calls are sent to WCDMA. Therefore the heuristic policy uses scheme *i* for the first stage, and scheme *iii* for the second stage, that is, compares the occupancy on each technology and sends calls to the one with the lowest value.

Figure 2.12 compares the blocking function of the heuristic policy and Policy #2 for the same values of Fig.2.5. It is evident that for the lowest values of λ_v, the heuristic policy is better than Policy #2, but this changes when $\lambda_v > 0.035$. This occurs because Policy #2 always sends calls to TDMA, and this behavior is similar to what is done by the optimal solution as λ_v grows (Section 2.2.2). The same could be said for Fig.2.13, where the throughput is the optimization function. In this case the improvement of the heuristic solution over Policy #2 is very small, but it is maintained while $\lambda_v < 0.041$. When this value is reached, Policy #2 is better than the heuristic solution because of its similarity to the optimal solution.

Figure 2.14 compares the heuristic solution with Policy #2 and the optimal solution, when the blocking function is optimized and λ_d changes. In this

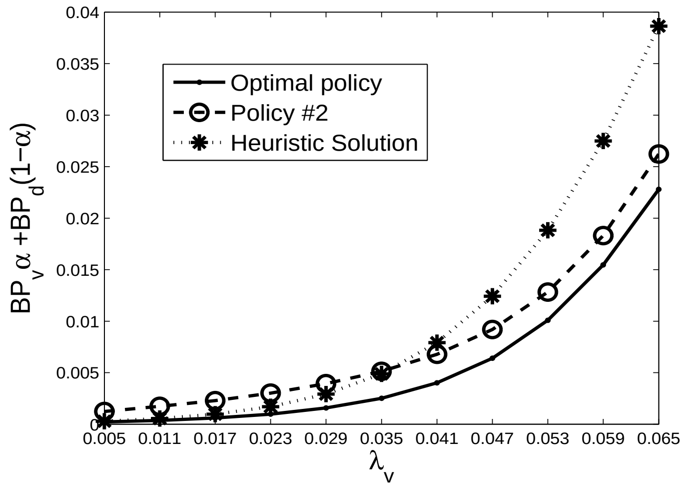


Figure 2.12: Blocking function for various λ_v.

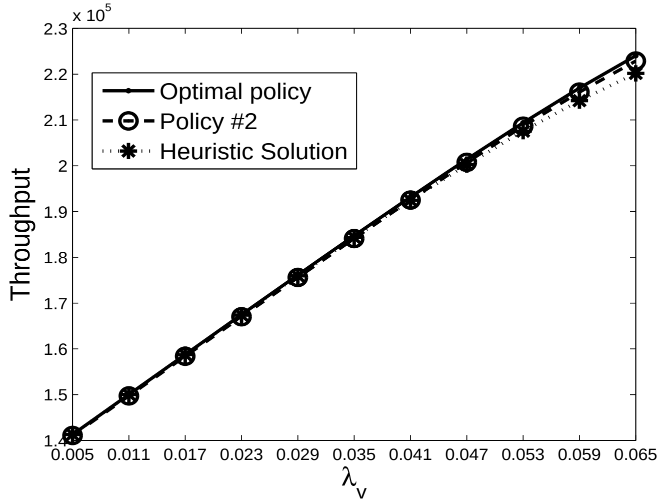


Figure 2.13: Throughput for various λ_v.

case, for the lowest values of λ_d Policy #2 is better than the heuristic, but once λ_d>0.08, the heuristic is better. This can be explained by the fact that the optimal solution sends more data calls to WCDMA as λ_d grows, and while Policy #2 always sends data calls to TDMA, the heuristic policy may send some calls to WCDMA according to occupation on each technology.This behavior has the same effect over the throughput as can be seen on Fig.2.15, where it is compared the throughput for the heuristic solution and Policy #2. For the lowest values of λ_d, Policy #2 is better than the heuristic, but when $\lambda_d > 0.65$ the heuristic solution has a higher throughput. Therefore the heuristic policy represents some advantages over the best fixed policy when data load is high, but its behavior is not as good as that of Policy #2 when voice load is high.

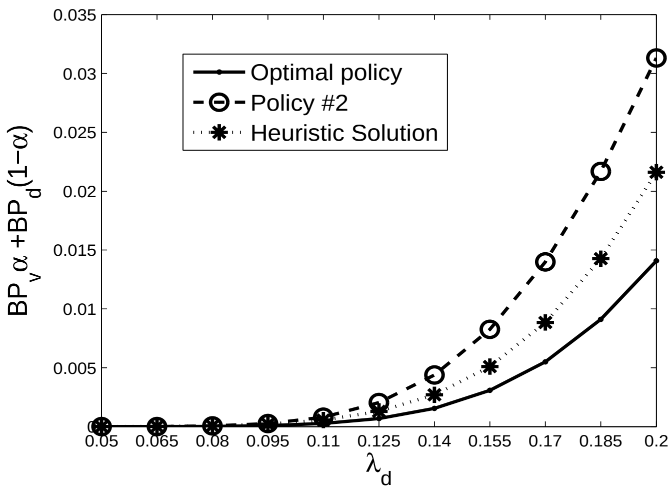


Figure 2.14: Blocking function for various λ_d.

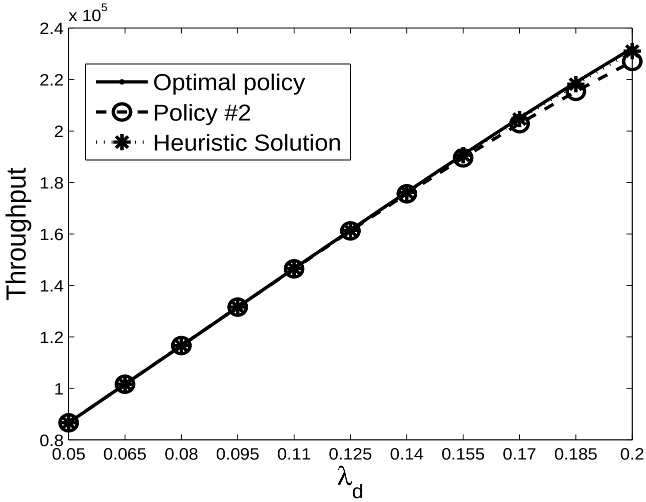


Figure 2.15: Throughput for various λ_d.

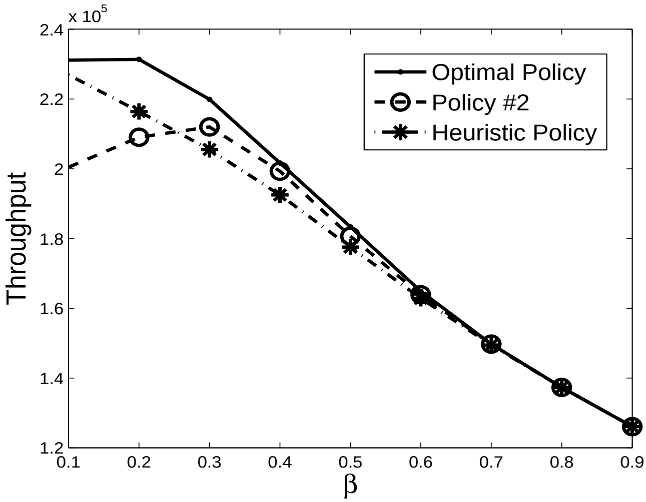


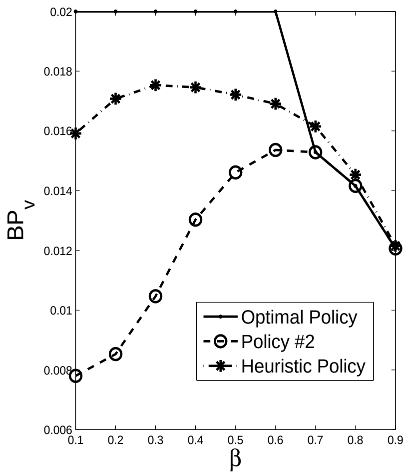
Figure 2.16: Throughput as a function of β.

2.2.4 Throughput optimization with QoS constraints

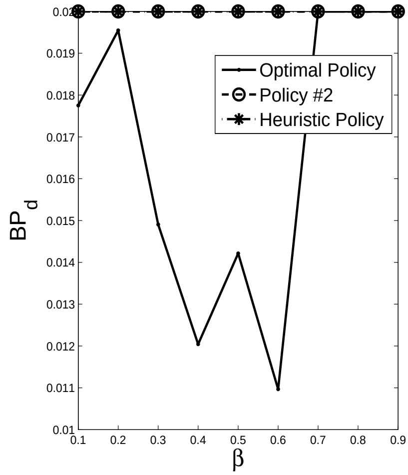
In this section we compare the policies in terms of the maximum arrival they can support subject to QoS constraints. Until now, we considered throughput optimization independent of other factors, but to provide QoS, it is necessary to limit both PB_v and PB_d. To do this, we defined the parameter β, which is the fraction of λ_v over the total arrival rate λ_T, that is, λ_v=$\lambda_T \cdot \beta$ and λ_d=$\lambda_T \cdot$ $(1 - \beta)$. In Fig.2.16 it is shown the throughput as a function of β for three policies: The optimal policy when we optimize the throughput, Policy #2, and the heuristic policy defined in the last section. It has to be considered that even when they share the same value of β, the arrival rates differ for each policy according to the restrictions imposed by the blocking probabilities (max 2 %). For example, when β=0.2, the total arrival rate λ_T that the optimal policy can handle is 0.2158, while it is of 0.2018 for the heuristic policy and 0.1945 for Policy #2. Therefore, the optimal policy is able to receive a higher arrival rate for voice and data calls while maintaining PB_v and PB_d below 2 %. Figures 2.17(a) and 2.17(b) show the voice and data blocking probabilities for different values of β. It can be seen that the optimal policy is the only one able to change its active constraint between PB_v and PB_d, taking advantage of the contribution of data calls on the throughput. This cannot be done by the other two policies, which penalize PB_d=0.2 for every β. As for the heuristic policy, it shows a higher maximum throughput for low values of β than Policy #2, and this behavior is reversed as β grows when voice calls are more important in order to maximize throughput, a behavior consistent with the results of the previous section.

2.3 Optimal policies for multiaccess networks with vertical handoff

So far, we have analyzed a system where no vertical handoff is used (now referred to as NVH), i.e. a call is served in the same technology where it



(a) *VoiceBlocking Probability.*



(b) *DataBlocking Probability.*

Figure 2.17: Blocking probabilities for various β.

was accepted. However, vertical handoff is considered an important feature in common radio resource management that improves the use of resources. In Table 2.4 we introduce four types of vertical handoff based on the analysis done in previous sections, where N is the necessary number of data calls such that one voice call can access WCDMA.

All types of vertical handoff are based on the results obtained in Sections 2.2.1 and 2.2.2, but the first two types are triggered by the arrival of a call, while the other two occur when a call is served. This distinction is important, since it affects the construction of the new Markov decision processes. The addition of types I and II of vertical handoff to NVH defines VH-A. The Markov model for this system has the same state space S of NVH, since restrictions (2.1) and (2.2) are not affected by vertical handoff. The same applies for the Markov model of system VH-B, which uses all types of vertical handoff (I-IV). However, the set of actions A and the transitions associated to them do change. For VH-A, a decision is made each time a call arrives as can be seen

in Table 2.3 and in Figure 2.18, where actions 0,1 and 2 do not include vertical handoff, while actions 3 and 4 correspond to vertical handoff types I and II respectively. For action 3, the value N is the number of data calls that need to be moved so that a new voice call can access WCDMA according to (2.2). The same applies for system VH-B, which includes vertical handoff types III and IV. The reason why handoff types III and IV do not affect the set A is that decisions are made only when a call arrives. In our model, handoffs triggered by service completion are done every time their specific conditions are fulfilled, so there are no decisions involved.
With this in mind, and using the same cost functions of (2.4) and (2.5), two new MDPs are constructed. These new MDPs will show the improvement when vertical handoff is included, where the MDP based on VH-A uses handoff when calls arrive and the MDP based on VH-B uses handoff for both arrivals and departures.

Table 2.3: set of actions A for MDPs with vertical handoff

value	*action*
0	Block call
1	Send call to TDMA
2	Send call to WCDMA
3	VH for N data calls from WCDMA to TDMA and the voice call is sent to WCDMA.
4	VH for 1 voice call from TDMA to WCDMA and the data call is sent to TDMA.

Type	*Triggering Event*	*Conditions*	*Number / Class of calls*	*From* $\Rightarrow$ *To*	*NVH*	*VH-A*	*VH-B*
I	voice **arrival**	Full occupation on WCDMA	N **data** calls	WCDMA$\Rightarrow$TDMA	–	✓	✓
II	data **arrival**	Channel sharing on TDMA	One **voice** call	TDMA$\Rightarrow$WCDMA	–	✓	✓
III	voice or data **departure** from WCDMA	Channel sharing on TDMA	One **voice** call	TDMA$\Rightarrow$WCDMA	–	–	✓
IV	voice or data **departure** from TDMA	VH does not produce channel sharing on TDMA	One **data** call	WCDMA$\Rightarrow$TDMA	–	–	✓

Table 2.4: Vertical Handoff Types

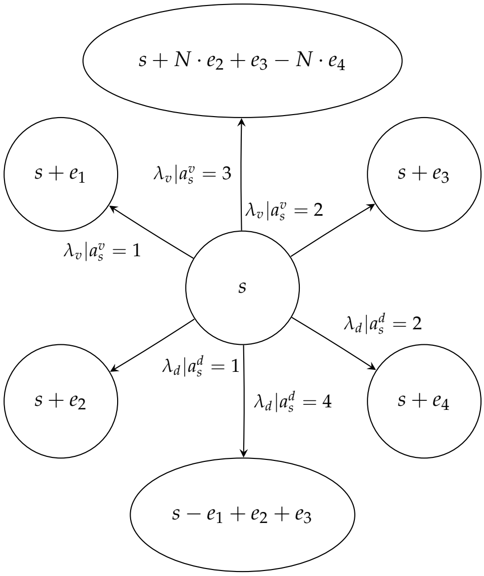


Figure 2.18: Transitions for voice and data arrivals using VH.

2.3.1 Optimal policy using vertical handoff

In the last section were introduced two new systems that included vertical handoff: VH-A and VH-B. The difference between them is that VH-B includes vertical handoff for users departures. In this section we use two new MDPs that are based on VH-A (MDP VH-A) and VH-B (MDP VH-B), and compare results with those obtained with the MDP for the NVH system (MDP NVH). It is our interest to study the impact that vertical handoff has over the optimal solutions and performance. Using the scenario specified in Table 2.2 for MDP VH-A and MDP VH-B, it is possible to extract the main characteristics of the optimal solutions as different parameters vary. Results for optimization of the blocking function defined in (2.4) while λ_v varies from 0.005 to 0.095 are summarized in Table 2.5. In general, the behaviour for voice and data calls are very similar in both MDPs. Nevertheless, some minor differences change the structure of the optimal solutions, and that has an important impact on the results obtained. Optimal solutions for MDP VH-A show a lower percentage of unused states than those solutions obtained using MDP VH-B. This is because Vertical Handoff types III and IV organize calls in such a way that a larger number of states from set S are left unused. When λ_v=0.005 the percentage of unused states is three times higher for the solution obtained with MDP VH-B than for the one obtained with MDP VH-A, and while this difference shortens when λ_v= 0.095, the percentage of unused states grows. This growth shows that an organized use of resources is necessary in order to obtain the optimal solution in both MDPs. Also, it may occur some voice blocking when there are resources available, but this behavior is expected only for the highest values of λ_v, when its influence is higher on the optimization function.

Similar results are obtained for optimization of the blocking function defined in (2.4) when λ_d varies from 0.05 to 0.225. Voice and data calls use Vertical Handoff types I and II respectively, but the percentage of unused states follows a different pattern. As λ_d grows, the percentage of unused states for the optimal solutions obtained with MDP VH-A remains constant, and it decreases for the solutions of MDP VH-B. This decrease shows that Vertical Handoff types III and IV allow more flexibility on how resources are managed, because a higher data arrival rate demands that more data calls share channels in order to reduce the blocking probability, something that cannot be done as successfully by only using Vertical Handoff types I and II. Also, for the highest values of λ_d, some states decide to block data calls even when there is capacity left, in order to save space for voice calls. However, the percentage of states doing this is below 3% for both MDPs. A summary of these results is shown in Table 2.6.

Using the scenario specified in Table 2.2 and the throughput optimization function defined in (2.5) while λ_v varies from 0.005 to 0.095, the optimal policies for MDP VH-A and MDP VH-B are summarized in Table 2.7. Again, voice and data calls use vertical handoff types I and II respectively in both MDPs. For the lowest values of λ_v, both MDPs decide to block voice calls (<1%) in order to enhance throughput, since data calls contribute more to the total throughput. However, this situation changes as λ_v grows when voice calls are accepted as long as it is possible. On the other hand, the percentage of unused states differs for each MDP. For MDP VH-A, the percentage of unused states grows with λ_v from 16% to 41.7%. On the other hand, for MDP VH-B, the percentage of unused states diminishes from 61.2% to 49.5% as λ_v grows.

The optimal policies for MDP VH-A and MDP VH-B as λ_d varies from 0.05 to 0.225 are summarized in Table 2.8.Voice and data calls use vertical handoff types I and II respectively in both MDPs. For the highest values of λ_d MDPs decide to block some voice calls, even though in a very small percentage (<1%). This is done in order to accept more data calls since they contribute more to the total throughput. For both MDPs the percentage of unused states grows with λ_d, and it is always higher for MDP VH-B.

		MDP VH-A	MDP VH-B
Voice calls	Lowest λ_v	• Sent to WCDMA or VH type I is used. • 10.4% of states are not used.	• Sent to WCDMA or VH type I is used. • 32.1% of states are not used.
	Highest λ_v	• Sent to WCDMA or VH type I is used. • 41.7% of states are not used. • Blocked in 1.00% of usable states.	• Sent to WCDMA or VH type I is used. • 50.4% of states are not used. • Blocked in 1.2% of usable states.
Data calls	Lowest λ_v	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 10.4% of states are not used.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 32.1% of states are not used.
	Highest λ_v	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 41.7% of states are not used.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 50.4% of states are not used.

Table 2.5: Main characteristics of the optimal solutions for the blocking function for various λ_v.

		MDP VH-A	MDP VH-B
Voice calls	Lowest λ_d	• Sent to WCDMA or VH type I is used. • 41.6% of states are not used.	• Sent to WCDMA or VH type I is used. • 49.4% of states are not used.
	Highest λ_d	• Sent to WCDMA or VH type I is used. • 41.6% of states are not used.	• Sent to WCDMA or VH type I is used. • 39.6% of states are not used.
Data calls	Lowest λ_d	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 41.6% of states are not used.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 49.4% of states are not used.
	Highest λ_d	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 41.6% of states are not used. • Blocked in 2.56% of usable states.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 39.6% of states are not used. • Blocked in 2.98% of usable states.

Table 2.6: Main characteristics of the optimal solutions for the blocking function for various λ_d.

		MDP VH-A	MDP VH-B
Voice calls	Lowest λ_v	• Sent to WCDMA or VH type I is used. • 16% of states are not used. • Blocked in 0.71% of usable states.	• Sent to WCDMA or VH type I is used. • 61.2% of states are not used. • Blocked in 0.25% of usable states.
	Highest λ_v	• Sent to WCDMA or VH type I is used. • 41.7% of states are not used.	• Sent to WCDMA or VH type I is used. • 49.5% of states are not used.
Data calls	Lowest λ_v	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 16% of states are not used.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 61.2% of states are not used.
	Highest λ_v	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 41.7% of states are not used.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 49.5% of states are not used.

Table 2.7: Main characteristics of the optimal solutions for throughput for various λ_v.

		MDP VH-A	MDP VH-B
Voice calls	Lowest λ_d	• Sent to WCDMA or VH type I is used. • 41.6% of states are not used.	• Sent to WCDMA or VH type I is used. • 45.4% of states are not used.
	Highest λ_d	• Sent to WCDMA or VH type I is used. • 43% of states are not used. • Blocked in 0.7% of usable states.	• Sent to WCDMA or VH type I is used. • 47.2% of states are not used. • Blocked in 0.56% of usable states.
Data calls	Lowest λ_d	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 41.6% of states are not used.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 45.4% of states are not used.
	Highest λ_d	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 43% of states are not used.	• Sent to TDMA while no sharing is needed. If so, VH type II is used or sent to WCDMA. • 47.2% of states are not used.

Table 2.8: Main characteristics of the optimal solutions for throughput for various λ_d.

Result analysis for vertical handoff MDPs

In this section we propose two new heuristic policies, which exploit the characterization of the optimal policies obtained from MDP VH-A and MDP VH-B that was described in the previous section. Heuristic policy VH-A makes use of vertical handoff types I and II, as it was seen for the optimal policies found using MDP VH-A. On the other hand, heuristic policy VH-B also includes vertical handoff types III and IV, as it was done by the optimal policies obtained using MDP VH-B. Both heuristic policies are defined in Table 2.9. Our objective is to compare the performance obtained by the two new heuristic policies with the one obtained by the optimal policies of the MDPs. The evaluation scenario is defined by Table 2.10. The comparative study also includes the three heuristic policies previously proposed in the literature, that were defined earlier in Section 3. In this new scenario, the maximum capacity for voice and data sessions in WCDMA are 71 and 28 respectively, so the capacity has grown over 6 times over the system described in Table 2.2. However, the computational cost does not grow linearly. Using a desktop personal computer, it took around 1 min to find the optimal policy of a single load point for the small system, while it took around 6 h in this system. Therefore, the calculation time of the optimal policies makes them unfeasible for online use. It should be noted that this is not an issue for the heuristic schemes that can be used as a JCAC algorithm.

Fig. 2.19 shows the blocking function for the three MDPs, the two heuristics and the three fixed policies when λ_v varies from 0.09996 to 0.4998 and λ_d=0.448. The blocking function value when λ_v=0.4998 is reduced to less of the half of the value of Policy #2 when the heuristic policies are used, and this improvement is more visible when comparing to the other fixed policies. Also, it should be noted that the heuristic policies may even improve over the optimal solution of MDP NVH as λ_v grows. The improvement of the blocking function has an effect in the aggregated throughput, which raises to 1.156 Mbps for Heuristic VH-A while it only reaches 1.116 Mbps for Policy #2 when λ_v=0.4998. Therefore under these conditions, using an heuristic

Heuristic policy	*Event*	*Action*
VH-A	Voice arrival	• Send to WCDMA. • If it is not possible, use VH type I. • If it is not possible, send to TDMA.
	Data arrival	• Send to TDMA if no channel sharing is needed. • If there is channel sharing, use VH type II. • If it is not possible, send to WCDMA. • If it is not possible, send to TDMA.
VH-B	Voice arrival	• Send to WCDMA. • If it is not possible, use VH type I. • If it is not possible, send to TDMA.
	Data arrival	• Send to TDMA if no channel sharing is needed. • If there is channel sharing, use VH type II. • If it is not possible, send to WCDMA. • If it is not possible, send to TDMA.
	Voice departure	• Use VH type III if departs from WCDMA • Use VH type IV if departs from TDMA
	Data departure	• Use VH type III if departs from WCDMA • Use VH type IV if departs from TDMA

Table 2.9: Definition for Heuristic policies with vertical handoff.

Table 2.10: New study Scenario.

WCDMA	TDMA
W=3.84 Mcps	$C = 8$
$(E_b/N_0)_v$=6.5 dB	n_c= 3
$(E_b/N_0)_d$=5 dB	$BR_{t,v}$=12.2 kbps
$BR_{w,v}$=12.2 kbps	$BR_{t,d}$=44.8 kbps
$BR_{w,d}$=44.8 kbps	
η_{ul}= 1	

Clients
μ_v= 0.0083
σ= 1 Mb

policy represents an improvement of 40 kbps, close to one data channel, or 3 voice channels, with blocking probabilities of 2.2 % and 1.8 % for data and voice, while Policy #2 raises them to 6.5% and 4.6%, respectively. Fig. 2.20 shows the blocking function for the MDPs, the heuristics and the fixed policies when λ_d varies from 0.3584 to 1.792 and λ_v is 0.0833. The blocking function values are lower for the heuristic functions when compared to the fixed policies, but they are higher than those obtained by MDP NVH when $\lambda_d > 1.0752$. However, when λ_d=1.792, the total throughput for heuristic VH-A is of 1.4896 Mbps and of 1.466 Mbps for MDP NVH. That is, the heuristic solutions cannot diminish the value of the blocking function for the higher values of λ_d as much as MDP NVH does, but they still raise the throughput, even though this is not the objective function. As in the case when λ_v varies, the differences for both heuristics are not very significant.

In Fig. 2.21 the voice and data blocking probabilities for the different policies when λ_v varies from 0.09996 to 0.4998 and λ_d=0.448 and the blocking function is optimized. It can be seen that the proportion of blocked users for each service in the heuristic solutions is below 2% for all the traffic ranges,

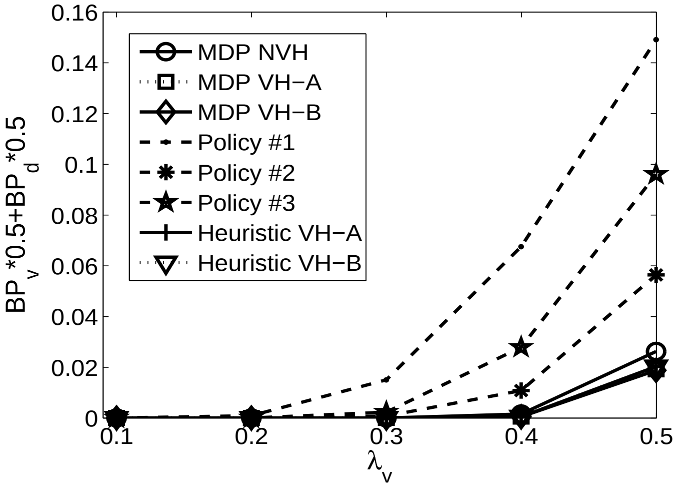


Figure 2.19: Blocking function for various λ_v.

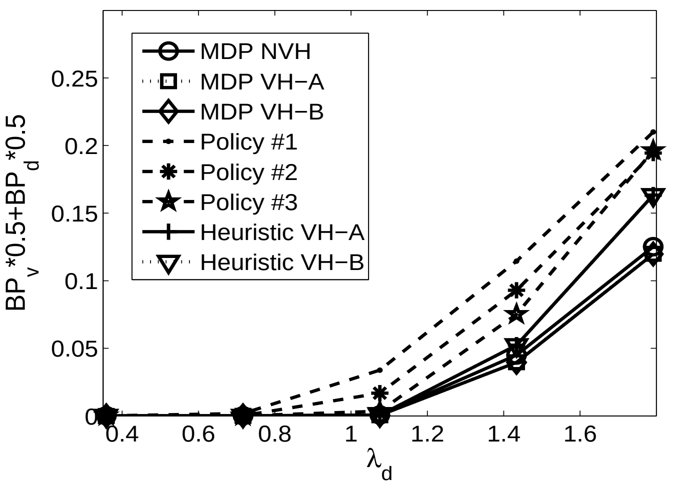
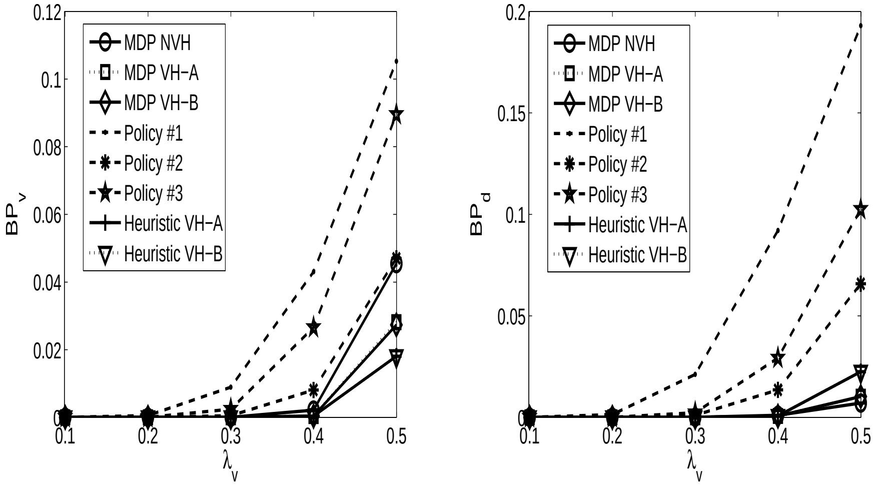


Figure 2.20: Blocking function for various λ_d.



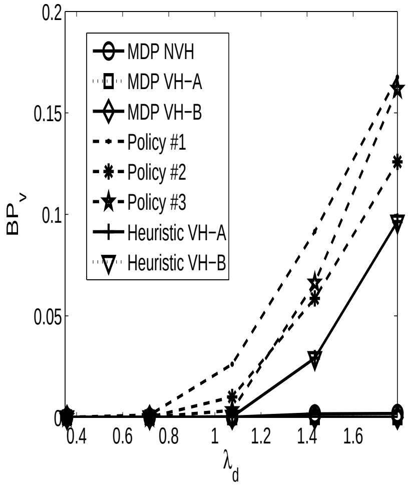
(a) *VoiceBlockingProbability.* (b) *DataBlockingProbability.*

Figure 2.21: Blocking Probabilities for various λ_v

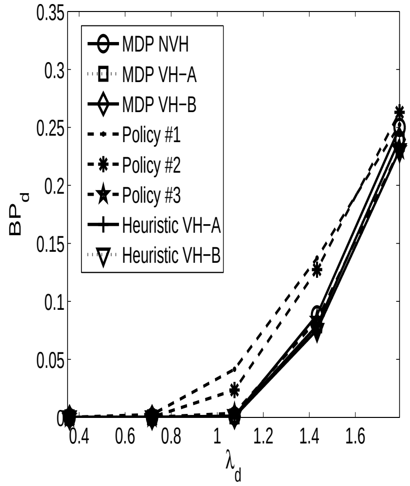
which clearly indicates fairness among both services. In fact, although the total blocking probability is higher for the heuristic solutions than for MDP VH-A and MDP VH-B, the heuristic solutions are able to share the blocking probabilities among the two services by increasing PB_d and reducing PB_v.

In Fig. 2.22 the voice and data blocking probabilities for the different policies when λ_d varies from 0.3584 to 1.792 and λ_v is 0.0833. In this case the fairness of the heuristic solutions is clearer, since while reducing the total blocking probability function, lets both blocking probabilities to grow proportionally. This is not the case of the MDPs that are able to succesfully maintain BP_v low, while letting PB_d grow, showing advantages for voice users.

The optimal throughput for the MDPs, as well as the throughput obtained by the heuristic solutions and the fixed policies as λ_v grows from 0.09996 to 0.4998 keeping λ_d=0.448 is shown in Fig. 2.23. There is an improvement of throughput of the heuristic solutions not only over the fixed policies, but



(a) *VoiceBlockingProbability*.



(b) *DataBlockingProbability*.

Figure 2.22: Blocking Probabilities for various λ_d

also over the optimal solutions of MDP NVH. Although the improvement in throughput is small when λ_v=0.4998, 12 kbps over MDP NVH and more when compared to the fixed policies, it is significant when we consider that the voice and data blocking probabilities of Heuristic VH-A are of 2.2% and 1.8% respectively, while these probabilities are of 1.5% and 3.8% for MDP NVH, and raise to a range of 6.5–19.5% and 4.6–10.5% for the fixed policies. That is, the heuristic solutions are able to improve throughput while maintaining low blocking probabilities (around 2%), and the other policies are not.

Fig. 2.24 shows the throughput for the MDPs, the heuristics and the fixed policies when λ_d varies from 0.3584 to 1.792 and λ_v is 0.0833. As observed, there is not too much room for the improvement of the throughput when λ_d varies, since most policies obtain similar values. The only real difference is seen when λ_d = 1.792, where the MDPs raise around 6 Kbps over the

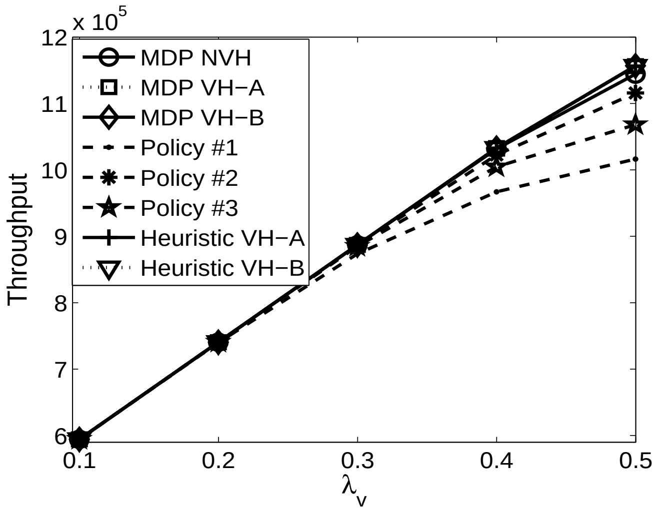


Figure 2.23: Throughput for various λ_v.

other policies. Since this is achieved by blocking all the voice sessions, this policies cannot be considered useful. It is interesting to see that the heuristics still achieve a higher throughput than all fixed policies, while keeping lower voice and data blocking probabilities. However, when λ_d = 1.4336, the voice and data blocking probabilities of the heuristic policies are of 5% and 2.9% for data and voice. Thus this load point could be considered a practical load limit.
In summary, we may conclude that the difference between the performance of the optimization functions achieved by the heuristic and optimal policies is negligible, and this negligible difference is consistent for both optimization criteria and a wide range of system parameters values.

Model validation

In order to validate the performance of the heuristic policies found, which were determined analytically, we evaluate them also by discrete event sim-

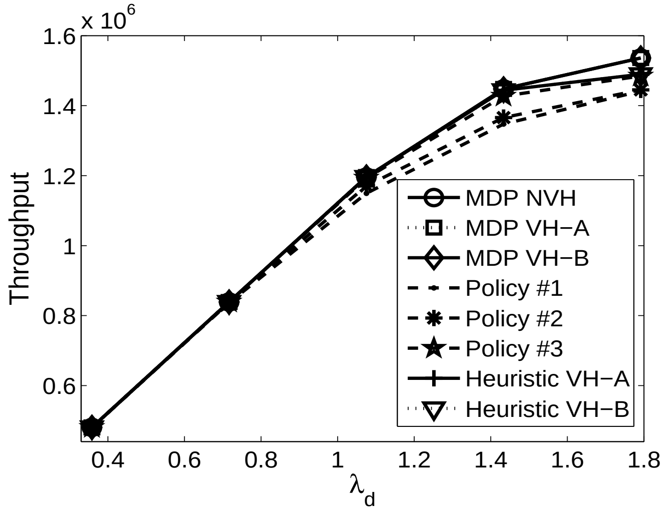


Figure 2.24: Throughput for various λ_d.

ulation. Three different distributions for the service time of voice sessions T_v and data size (σ) were used, namely, exponential, hyper-exponential and Erlang. We set the coefficients of variation of the last two to 2 and 0.5, respectively. The exponential distribution is known to have a coefficient of variation equal to 1. Clearly, the mean of all distributions coincides for each load point. Our purpose here is not only to establish the correctness of our mathematical analysis, but also to assess the impact of the exponentially distributed data size and voice service time assumptions.

The simulation results for different distributions of the data size using the heuristic policy VH-A are shown in Figs. 2.25 and 2.26. As observed, there is an excellent agreement between the analytical and simulation results for all distributions. The same applies for the simulation results of the heuristic policy VH-B, shown in Figs. 2.27 and 2.28.An interesting and very important finding is that the performance of the heuristic policies is insensitive to distribution of the data size beyond its mean. Although not shown, an identical conclusion is obtained with respect to the insensitivity of the system

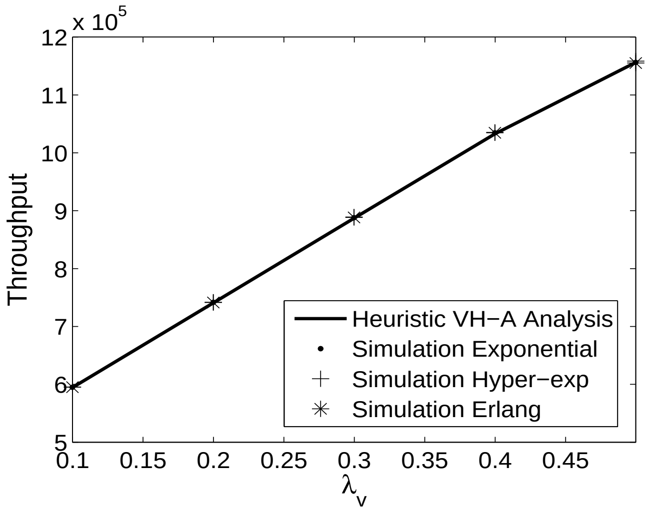


Figure 2.25: Simulation vs Analysis results of throughput as λ_v varies.

performance with respect to the distribution of the voice service time.

2.3.2 Cost of the vertical handoff

In the previous section we introduced four types of vertical handoffs and used them to find new optimal policies. We also designed two new heuristic policies and showed that they outperform the optimal policies obtained for a system without vertical handoffs. The main issue in this section is to explore the impact that session blocking and vertical handoff costs have on the optimal policies. In order to do this, we define the objective function

$$F_{VH} = \theta \cdot \zeta_{VB} + (1-\theta) \cdot \zeta_{DB} + C_{VH} \cdot \zeta_{VH}, \tag{2.7}$$

where θ, $0 \leq \theta \leq 1$, is the factor that defines the cost for blocking a single voice or data call, and ζ_{VB} and ζ_{DB} are the mean voice and data blocking rates. In the same way, C_{VH} is the cost of performing a single vertical handoff, and ζ_{VH} is the mean rate of vertical handoffs performed. Hence, by assigning

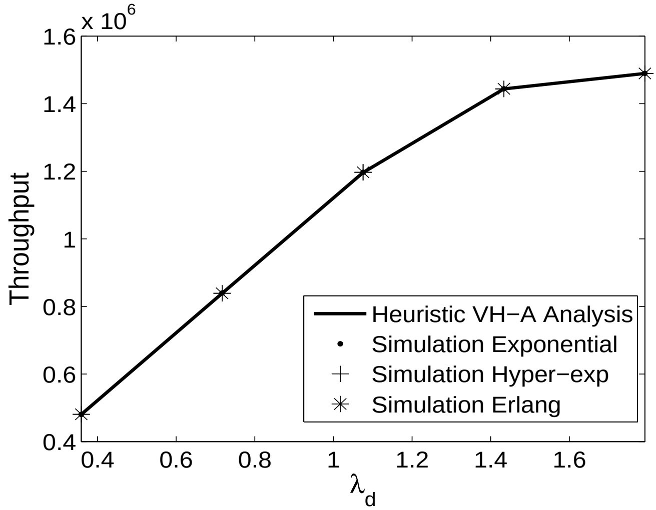


Figure 2.26: Simulation vs Analysis results of throughput as λ_d varies.

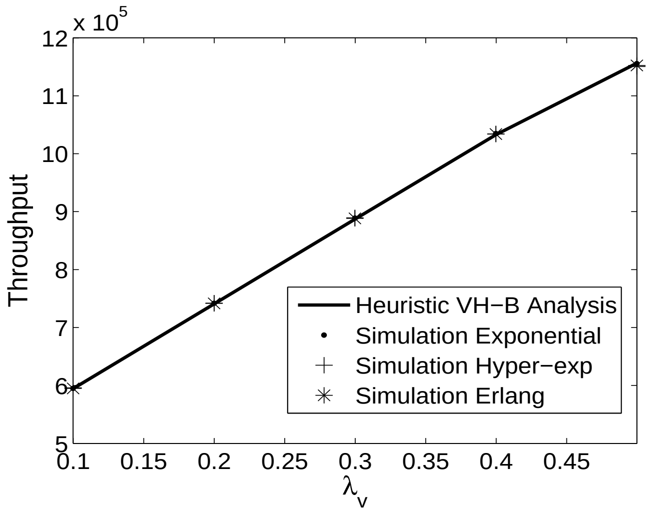


Figure 2.27: Simulation vs Analysis results of throughput as λ_v varies.

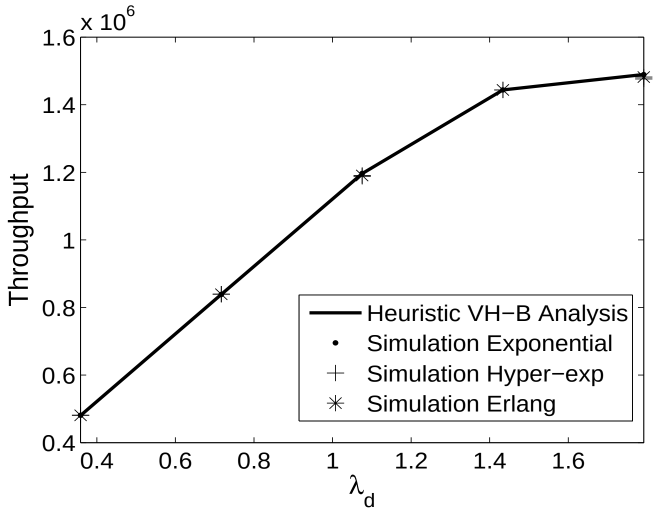


Figure 2.28: Simulation vs Analysis results of throughput as λ_d varies.

values to θ and C_{VH}, a new optimal policy that minimizes F_{VH} can be found by solving the appropriate MDP.

Markov decision process for vertical handoff cost

In this section we define three new MDPs based on (2.7). The first one does not use vertical handoff (MDP BR), the second one uses vertical handoff types I and II (MDP C1), and the last one uses all four types of vertical handoff (MDP C2). These MDPs are different from those exposed in Section 2.3 because of their objective functions. The state space for all of them S is defined by (2.1) and (2.2) and the set of actions a is that of Table 4.1 for MDP BR and that of Table 2.3 for MDP C1 and MDP C2. The cost function associated to the objective function for each feasible state $\boldsymbol{s}$ for MDP BR is

$$\mathrm{cost}(\boldsymbol{s}) = \lambda_v \cdot G(a_s^v) \cdot \theta + \lambda_d \cdot G(a_s^d) \cdot (1 - \theta), \tag{2.8}$$

for MDP C1 is

$$\begin{aligned}\mathrm{cost}(\boldsymbol{s}) = {}& \lambda_v \cdot G(a_s^v) \cdot \theta + \lambda_d \cdot G(a_s^d) \cdot (1-\theta) \\ & + C_{VH} \cdot (\lambda_v \cdot R(a_s^v) + \lambda_d \cdot R(a_s^d)), \end{aligned} \tag{2.9}$$

and for MDP C2 is

$$\begin{aligned}\mathrm{cost}(\boldsymbol{s}) = {}& \lambda_v \cdot G(a_s^v) \cdot \theta + \lambda_d \cdot G(a_s^d) \cdot (1-\theta) \\ & + C_{VH} \cdot \Big(\lambda_v \cdot R(a_s^v) + \lambda_d \cdot R(a_s^d)\Big) \\ & + C_{VH} \cdot \Big(T(\boldsymbol{s}_{TDMA}^v) + T(\boldsymbol{s}_{TDMA}^d) \\ & + T(\boldsymbol{s}_{WCDMA}^v) + T(\boldsymbol{s}_{WCDMA}^d)\Big), \end{aligned} \tag{2.10}$$

where the coefficients are explained in Table 2.11.

Result analysis

As before, policy iteration is used to solve the MDPs. The reference scenario is defined in Table 2.2 with θ= 0.5, i.e. the cost of blocking voice and data calls is the same. Fig. 2.29 shows the optimal cost for each of the different MDPs studied as C_{VH} varies. MDP C2 has the lowest optimal cost when C_{VH}=0, and is followed closely by MDP C1. However, as C_{VH} grows, the cost of MDP C2 grows rapidly, surpassing MDP C1 and MDP BR. This is explained by the large amount of vertical handoffs of types III and IV performed by MDP C2 policies. In fact, for values of C_{VH} as low as 0.01, the optimal policy obtained by MDP C2 is more costly than the one obtained by MDP BR. As the cost of blocking voice and data sessions is 0.5, we could say that it would make sense to use the policies obtained by MDP C2 only when the cost of a vertical handoff is 50 times lower than the cost of blocking a voice or data sessions. On the other hand, the costs of MDP C1 policies vary slowly and are bounded by those of MDP BR. This occurs because if the objective function growth is caused by a vertical handoff, then the MDP C1 policy can always choose not to use it, which makes the MDP C1 policies tend to the

SYMBOL	DEFINITION	VALUE
$G(a_s^x)$	Indicates if $\boldsymbol{s}$ is a blocking state for service x	• If action a_s^x is blocking, $G(a_s^x)$=1. • Otherwise $G(a_s^x)$=0.
$R(a_s^x)$	Indicates the number of sessions that suffer VH when a session of service x arrives while the system is on state $\boldsymbol{s}$.	• If a_s^x=3, and all the conditions for VH type I are fulfilled, $R(a_s^v) = N$. • If a_s^x=4, and all the conditions for VH type II are fulfilled, $R(a_s^d) = 1$. • Otherwise, $R(a_s^x) = 0$.
$T(\boldsymbol{s}_{TDMA}^v)$	Indicates the rate of sessions that suffer VH when a voice session is served on TDMA while the system is on state $\boldsymbol{s}$.	• If the conditions for VH type IV are fulfilled once a voice session is served on TDMA, $T(\boldsymbol{s}_{TDMA}^v) = s_1 \cdot \mu_v$. • Otherwise $T(\boldsymbol{s}_{TDMA}^v) = 0$.
$T(\boldsymbol{s}_{TDMA}^d)$	Indicates the rate of sessions that suffer VH when a data session is served on TDMA while the system is on state $\boldsymbol{s}$.	• If the conditions for VH type IV are fulfilled once a data session is served on TDMA, $T(\boldsymbol{s}_{TDMA}^d) = \min(C\text{-}s_1, s_2) \cdot BR_{t,d}/\sigma$. • Otherwise $T(\boldsymbol{s}_{TDMA}^d) = 0$.
$T(\boldsymbol{s}_{WCDMA}^v)$	Indicates the rate of sessions that suffer VH when a voice session is served on WCDMA while the system is on state $\boldsymbol{s}$.	• If the conditions for VH type III are fulfilled once a voice session is served on WCDMA, $T(\boldsymbol{s}_{WCDMA}^v) = s_3 \cdot \mu_v$. • Otherwise $T(\boldsymbol{s}_{WCDMA}^v) = 0$.
$T(\boldsymbol{s}_{WCDMA}^d)$	Indicates the rate of sessions that suffer VH when a data session is served on WCDMA while the system is on state $\boldsymbol{s}$.	• If the conditions for VH type III are fulfilled once a data session is served on WCDMA, $T(\boldsymbol{s}_{WCDMA}^d) = s_4 \cdot BR_{w,d}/\sigma$. • Otherwise $T(\boldsymbol{s}_{WCDMA}^d) = 0$.

Table 2.11: Coefficients for vertical handoff cost optimization functions.

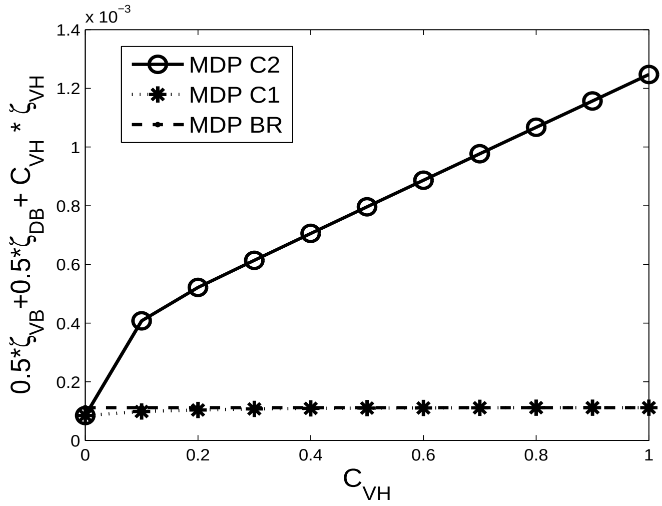


Figure 2.29: Optimization values for various C_{VH}.

ones obtained by MDP BR. The interesting point here is to find for which C_{VH} value both MDPs reach the same optimal policy, and therefore the same costs. This value is C_{VH}=0.9. Then, as before,we could say that it would make sense to use the policies obtained by MDP C1 only when the cost of a vertical handoff is not bigger that 1.8 times the cost of blocking a voice or data sessions. It is interesting to notice that when C_{VH}=0, the optimal policies of MDP C1 and MDP C2 are very similar to those of MDP VH-A and MDP VH-B, even though the objective functions are different. Therefore, performance parameters, such as throughput and blocking probabilities (BP_v and BP_d), are similar as well. As C_{VH} grows, the performance degrades, and this happens at a faster rate for the MDP C2 policies than for thew MDP C1 ones. Hence, while the ratio of voice/data blocking cost to C_{VH} is high, it is expected that the heuristic policies VH-A and VH-B fairly represent the optimal policies. This last remark is true even for higher ratio values in the case of MDP C1 and the heuristic VH-A, for the reasons explained earlier.

2.4 First iteration policies for multiaccess networks

Markov decision processes (MDPs) are widely used for control problems where revenues depend on episodic actions. Different solving methods are used, such as dynamic programming or reinforcement learning. In problems where the state space and the transition probabilities are well known, dynamic programming is a reliable method which allows to find the optimal solution for a given cost function. Dynamic programming algorithms such as policy iteration and value iteration are commonly used, where the former is able to find the optimal solution in less iterations than the latter, although some variations of value iteration can be done in order to reduce the necessary number of iterations as shown in [ZS05]. Different approximate methods have been proposed to reduce the computation complexity such as state aggregation [BC89] or linear approximations [SS85] applied to MDPs. However, these methods neither produce solutions that are necessarily close to the optimal, nor are efficient as it is stated in [Shl10]. In policy iteration, the optimal policy is found by choosing an initial random policy, evaluating its cost/reward through *policy evaluation* and enhancing it through *policy improvement*. This two-phase iteration is repeated until no further improvement can be done, i.e. the optimal policy is found. Although it is well known that policy iteration converges in a few steps, when the dimensionality (size of the state space) of the Markov process that models the system dynamics is large, the computational cost to obtain the optimal policy is also large. In [OK92] a first policy iteration solution is proposed, where the policy improvement phase is performed only once to obtain a suboptimal solution. This method drastically reduces the computational cost for large systems. In [vLAV01] a first iteration policy solution is proposed for a system where the cost to find a solution for an initial policy is low and it closely resembles the optimal.

In this section we also make use of the first iteration policy and compare its performance with the optimal solution for the radio resource management problem proposed in Section 2.1. The main objective of this work is the proposal and evaluation of two different methods to perform policy evaluation to obtain the first iteration policy. The first approach consists in iterating over the embedded discrete time Markov chain, which is found using uniformization [Gra77]. The second solution is a variation of the typical time scale decomposition, since it relates the steady state probabilities of the fluid regime with the transitions of the quasi-stationary regime. Results for both approaches are compared with the optimal solution, and a considerable reduction of the computational cost is achieved, while obtaining a good precision.

2.4.1 1st step policy iteration through the embedded discrete time Markov chain

In sections 2.2 and 2.3 various MDPs were solved using policy iteration for different scenarios through the LSQR algorithm [PS82], commonly used for large and sparse matrices. However, this method requires a large number of iterations and high internal precision to converge, which greatly increases its computational cost and thus reduces the scope of possible implementations. In this section we propose a method that partially alleviates the high computational cost by using the first step solution of policy iteration and the properties of the embedded discrete time Markov chain (eDTMC). The eDTMC can be obtained by dividing each outgoing transition rate by a factor γ which should be bigger than the largest aggregated outgoing transition rate. Then, a loop must be defined to keep the sum of transition probabilities equal to one. This method is known as uniformization [Gra77]. The main advantage of the eDTMC is that the steady state probability distribution (SSPD) can be easily found iteratively. Once the transition matrix T has been defined according to the initial policy Ψ_{ini}, the SSPD vector Π can be solved by iterating as follows:

$$\Pi_{ini}^{i+1} = \Pi_{ini}^{i} \cdot T(\Psi_{ini}), \tag{2.11}$$

where Π_{ini}^{0} is a vector of zeros with a 1 in its first position. Two stopping criteria have been defined: The quadratic error is lower than the limit δ,

$|\Pi_{ini}^{i+1} - \Pi_{ini}^{i}|^2 < \delta$, or the maximum number of iterations is reached, $i = it_{max}$. Having Π_{ini}, the mean cost of the initial policy $\bar{c}(\Psi_{ini})$ is found using:

$$\bar{c}(\Psi_{ini}) = BP_d \cdot (1 - \alpha) + BP_v \cdot \alpha. \tag{2.12}$$

This is needed to iteratively obtain the relative values of the initial policy $\vec{r}(\Psi_{ini})$, through Howard's equation as:

$$\vec{r}^{i+1}(\Psi_{ini}) = \vec{c}(\Psi_{ini}) - \bar{c}(\Psi_{ini})\vec{e} + T(\Psi_{ini})\vec{r}^{i}(\Psi_{ini}), \tag{2.13}$$

where $\vec{c}(\Psi_{ini})$ is a column vector with the cost of being in each state in S, $\vec{e}$ is a column vector of ones and $\vec{r}^{0}(\Psi_{ini})$ is a zeros vector of proper size. Two stopping criteria have been defined: The quadratic error is lower than the limit δ', $|\vec{r}^{i+1}(\Psi_{ini}) - \vec{r}^{i}(\Psi_{ini})|^2 < \delta'$, or the maximum number of iterations is reached, $i = it'_{max}$.

Once we have obtained the relative values of the initial policy $\vec{r}(\Psi_{ini})$, it is straightforward to perform *policy improvement* to obtain the actions a_n that define the first step policy Ψ_{fs} using:

$$\Psi_{fs}(a_n) = \arg\min \left\{ c_n(a_n) - \bar{c}(\Psi_{ini}) + \sum_m t_{n,m}(a_n) r_m(\Psi_{ini}) \right\}, \tag{2.14}$$

where $c_n(a_n)$ is the cost associated to being in state n and taking action a, $t_{n,m}(a_n)$ is the probability of going from state n to state m for the Markov chain that uses policy Ψ_{ini} with action a, and $r_m(\Psi_{ini})$ is the relative value of the destination state, m.

It should be noted that this method requires the setting of four parameters that have an important impact in Ψ_{fs}, that is, δ and it_{max} for Π_{ini}, and δ' and it'_{max} for $\vec{r}(\Psi_{ini})$. For very small values of δ and δ' or high values of it_{max} and it'_{max} the computational cost will increase but the obtained values will be closer to the real value, and the improved policy will be better. Therefore, it is necessary to define the values of δ, δ', it_{max} and it'_{max} that can guarantee an acceptable precision. In our experiments, unless otherwise stated, the chosen values were: $\delta = \delta' = 10^{-3}$ and $it_{max} = it'_{max} = 500$.

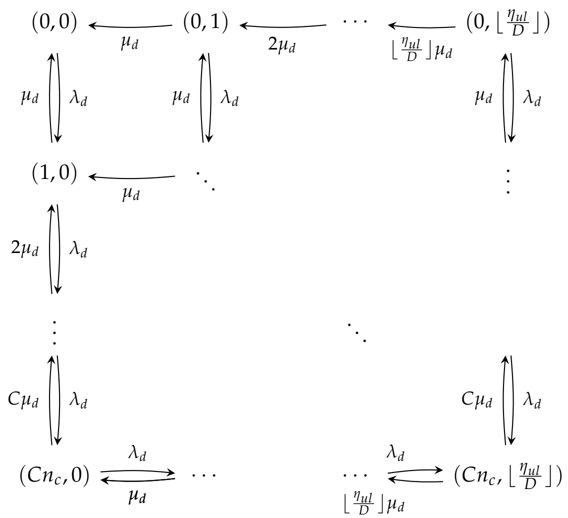


Figure 2.30: Continuous-time Markov chain for a fast time scale subsystem.

2.4.2 1st step policy iteration through time scale separation

Since the rate of events is higher for data users than for voice users, it is possible to assume that the former can see the latter as being still. By means of this approximation, an SSPD can be defined for each combination of data users $\boldsymbol{d}$=(d_1,d_2), where its state space is conditioned by (2.1) and (2.2) according to the combination of voice users (v_1,v_2), and the initial policy Ψ_{ini} chosen. Let us denote these conditional probabilities as $p((d_1, d_2)|(v_1, v_2))$. Unless otherwise stated, in this work Ψ_{ini} is a policy that sends voice calls to WCDMA until it is full, and then sends them to TDMA. On the other hand, data sessions are sent to TDMA until it is full, and then are sent to WCDMA. Since v_1={0,1,...,C} and v_2={0,1,...,$\lfloor \frac{\eta_{ul}}{V} \rfloor$}, a total of $(C + 1) \cdot (\lfloor \frac{\eta_{ul}}{V} \rfloor + 1)$ independent two-dimensional systems must be solved. The CTMC of the fast time scale subsystem (FTSS) conditioned to $v_1 = 0$ and $v_2 = 0$ is shown in Fig 2.30.

On the other hand, when the time scale separation is sufficiently large, data sessions can achieve a permanent regime between two voice events, and therefore it can be assumed that its behavior is sufficiently represented by its mean. However, this approach does not consider the capacity limitation that data users are imposing over voice users, that is, a transition between two states of the slow time scale subsystem (STSS) can only exist if the conditions in (2.1) and (2.2) are fulfilled on both the initial and final states. For example when TDMA is fully occupied by voice calls, and a new voice call arrives to WCDMA, being the initial and final states $v_o = (C, 0)$ and $v_f = (C, 1)$ respectively, the transition can only occur when d_1=0 and $d_2 \leq (\eta_{ul}$ - $V)$ / D, that is, the voice transition is limited by the subset of data sessions (d_1, d_2) that maintain capacity consistency according to (2.1) and (2.2) for both $v_o = (C, 0)$ and $v_f = (C, 1)$. In order to model this phenomenon, we use the conditional probabilities $p((d_1, d_2)|(v_1, v_2))$ that were calculated in the previous step. Hence, the transition rate of going from an initial STSS state to a final STSS state is weighted by the sum of probabilities of being on those FTSS states where both the initial and final STSS states are feasible according to (2.1) and (2.2). This procedure is similar to that proposed in [OARH06]. For the initial policy Ψ_{ini}, the weighting probabilities Φ_{v_o,v_f} for going from initial state v_o to final state v_f are:

$$\phi^W_{(v_1,v_2),(v_1,v_2+1)} = \sum_{d_1=0}^{n_c(C-v_1)} \sum_{d_2=0}^{\frac{\eta_{ul}-(v_2+1)V}{D}} p((d_1, d_2)|(v_1, v_2)), \qquad (2.15)$$

$$\phi^T_{(v_1,v_2),(v_1+1,v_2)} = \sum_{d_1=0}^{n_c(C-(v_1+1))} \sum_{d_2=0}^{\frac{\eta_{ul}-(v_2)V}{D}} p((d_1, d_2)|(v_1, v_2)), \qquad (2.16)$$

where ϕ^W is used for calls sent to WCDMA and ϕ^T is used for calls sent to TDMA. The resulting CTMC for the STSS using policy Ψ_{ini} is shown in Fig. 2.31, where elements $\boldsymbol{v}$=(v_1,v_2) represent that there are v_1 active voice sessions on TDMA and v_2 on WCDMA. It should be noted that voice calls are sent to WCDMA by default, and when capacity is full they are sent to TDMA. The STSS probability distribution p (v_1,v_2) is easily found by solving the two dimensional CTMC.

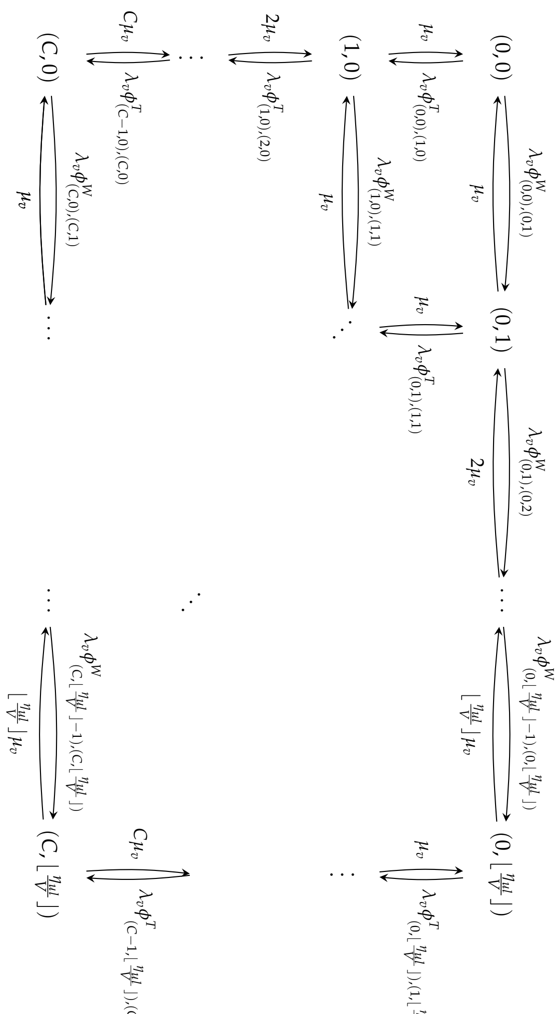


Figure 2.31: Continuous-time Markov chain for the slow time scale subsystem.

Using Ψ_{ini}, the SSPD for the complete system, Π_{ini}, is obtained by unconditioning $p((d_1,d_2)|(v_1,v_2))$ as follows:

$$\Pi(v_1,v_2,d_1,d_2) = p(v_1,v_2) \cdot p((d_1,d_2)|(v_1,v_2)). \tag{2.17}$$

Having Π_{ini} it is possible to obtain the mean cost of the initial policy $\bar{c}(\Psi_{ini})$ using (2.12) as it was done in the previous section. Also, we can perform *policy evaluation* by defining the discrete Markov chain of the whole system in order to solve the discrete version of Howard's equation in (2.13). To maintain consistency, the iterative solution uses the same values of the last section, that is, $\delta' = 10^{-3}$ and $it'_{max} = 500$. The first step of policy iteration is fulfilled by performing *policy improvement* as shown in (2.14) to obtain Ψ_{fi}. As it can be seen, the difference between both methods lies in how Π_{ini} is obtained, in order to perform *policy evaluation* and *policy improvement*. In this method, Π_{ini} is found solving multiple small sized continuous time Markov chains which are straightforward. While on the previous method, we had to define specific values for δ and it_{max} to reduce computational cost while at the same time maintaining a low error. In this solution, the influence that data user's occupancy have over the system's remaining capacity for voice users is modeled through the introduction of SSPD dependent transition rates, which expands the reach of time scale separation approaches.

2.4.3 Numerical Analysis

In previous sections we have defined two methods to find the steady state probability distribution of the initial policy, Π_{ini}, where the first method uses the embedded discrete time Markov chain and the second method uses a novel approach of time scale separation. In this section we compare the 1st step policy iteration solution of both approaches in terms of the computational cost and also in accuracy. The system is defined by the values in Table 2.2.

In Fig. 2.32 we compare the blocking function for the initial policy chosen for both approximation methods, with the solution obtained by the time scale separation approach, the embedded discrete time Markov chain approach and the optimal solution as λ_v varies from 0.0996 to 0.4498 and $\lambda_d = 0.448$. As it can be seen, with the 1st step of policy improvement, both approximate solutions are close to the optimal for low values of λ_v. However, when $\lambda_v = 0.4498$, it is necessary to perform more iterations in order to find a solution that is closer to the optimal. This occurs due to two reasons: First, when λ_v is high, the optimal solution will use vertical handoff as defined in actions 3 and 4 of Table 2.2 more often, while the initial policy does not use vertical handoff. Therefore, it is necessary to change more actions to get close to the optimal solution and this can only be done by performing at least three more policy improvement steps. Secondly, since λ_v is very high and voice calls are not allowed to share TDMA channels as data sessions do, once voice calls have occupied all the resources on WCDMA, they will tend to use more resources of TDMA, reducing the ability of data sessions to share and therefore increasing the blocking function. Hence, in this case the first step solutions are not limited by the approach we choose, but by the initial policy, and that is why both solutions are very similar.

In Fig. 2.33 we follow the same approach and compare the blocking function value for the initial policy with the solution obtained by the time scale separation approach, the embedded discrete time Markov chain approach and the optimal solution as λ_d varies from 0.3584 to 1.792 and $\lambda_v = 0.0833$. In this case, the 1st step of policy iteration is enough to obtain solutions that closely resemble the optimal, and this occurs for the whole range of λ_d. In this case the impact of vertical handoff in blocking probability is diminished by the ability of data sessions to share channels in TDMA.

So far we have seen that the solutions of both approaches are very similar for all the range of λ_v and λ_d. In Table 2.12, it is shown that the computational cost of both solutions is also very similar for each point of Figures 2.32 and 2.33 using a 2 Quad CPU @2.4GHz, 3.24 GB RAM desktop. Let us recall that the optimal solution for $\lambda_v = 0.4998$ and $\lambda_d = 0.448$ was obtained in $9724.99s$ after 4 steps, using the LSQR algorithm. Therefore, the proposed methods achieve a reduction to less than 10% of the original computational cost.

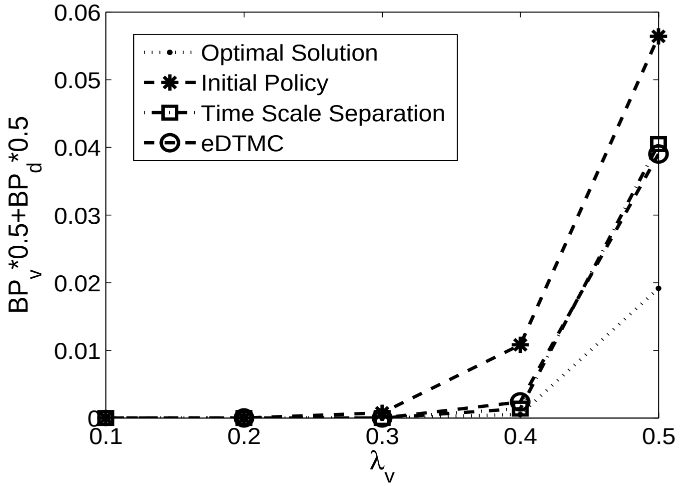


Figure 2.32: Blocking function for various λ_v.

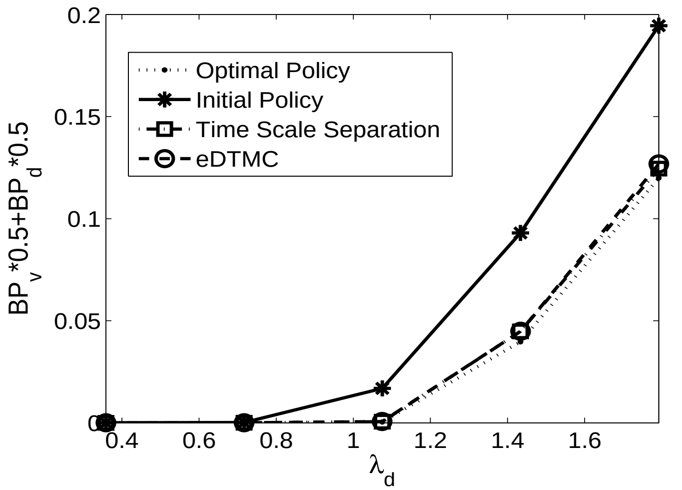


Figure 2.33: Blocking function for various λ_d.

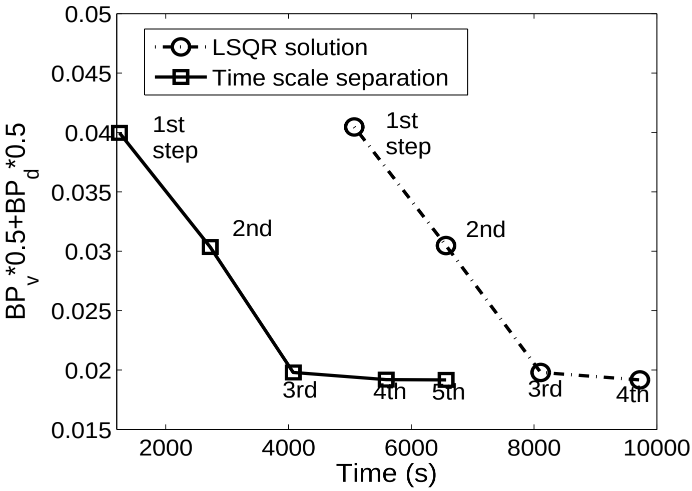


Figure 2.34: Computational cost of LSQR in CTMC vs 1st step time scale separation and eDTMC

The main advantage that the time scale separation approach has over the eDTMC approach is that it reduces the parameter set to be defined from four to two, which is important as was discussed in Section 2.4.1, specially if we want to perform more steps, since a high error in the first step will propagate into the next steps. In fact, selection of these parameters is so critical that if we maintain the values of $\delta = 10^{-3}$ and $it_{max} = 500$, and keep performing *policy iteration*, we will obtain a final blocking function value of 0.0392185 after three steps. This of course is far from the optimal solution, and very close to the value obtained in the 1st step policy, thus no real improvement has been done. This occurs because δ and it_{max} are not good enough to accurately perform *policy evaluation* and therefore the information used in *policy improvement* is flawed, and the error grows on each step performed.

In Fig. 2.34 we compare the blocking function value on each step of *policy improvement* for two solution methods: In the first solution, we use the 1st step time scale separation to obtain the initial mean cost and then perform several steps of *policy iteration* based on the eDTMC, but in this case the chosen values are $\delta' = 10^{-6}$ and $it'_{max} = 50000$. The second solution is based on the LSQR algorithm and uses a CTMC to solve the system. It should be noted that the initial policy in both cases is the one that will send voice calls to WCDMA and data sessions to TDMA. The values of $\lambda_v = 0.4998$ and $\lambda_d = 0.448$ were already used in Fig. 2.32, and the second method corresponds to the optimal solution showed there.

Since we increased the number of it_{max}, the cost of the 1st step policy is 1246.766s, over 70% more than the policies seen in figures 2.32 and 2.33. However, in this case after five steps we obtain a policy that closely resembles the optimal, with a blocking function value of 0.01917517 while the optimal has a value of 0.01917065, which means a relative error of $2.35 \cdot 10^{-3}$%. It is also worth noting that the policy obtained using the eDTMC reaches in the third step a blocking function value of 0.01980314, which is very close to the optimal but it was found in 4076.31s, about 1000s less than the time than it took to obtain the 1st step policy obtained using LSQR (5072.51s), which has a blocking function value of 0.04046063. Therefore, it can be seen that a significant reduction in computational cost and a close to optimal solution can be obtained using the proposed methods.

2.5 Conclusions

In this chapter we have studied a JCAC and JHC optimization problem for a system with two RATs (WCDMA and TDMA) and two services (voice and data). Two different optimization criteria were used, one based on the blocking probabilities of each service, and the other on the total throughput. We formulated the optimization problem using the formalism of Markov decision processes and used policy iteration to solve it.

Optimal policies have been found for various traffic scenarios using both optimization functions, and their performance was compared to the ones obtained by three fixed policies. We were able to characterize the optimal

Table 2.12: Solution times

	Time Scale Separation	eDTMC solution
λ_v=0.09996, λ_d=0.448	716.36 s	717.28 s
λ_v=0.1999, λ_d=0.448	719.85 s	687.67 s
λ_v=0.2999, λ_d=0.448	726.65 s	696.87 s
λ_v=0.3998, λ_d=0.448	723.09 s	678.19 s
λ_v=0.4998, λ_d=0.448	715.48 s	720.88 s
λ_v=0.0833, λ_d=0.3584	721.01 s	721.36 s
λ_v=0.0833, λ_d=0.7168	712.58 s	723.96 s
λ_v=0.0833, λ_d=1.075	747.34 s	724.46 s
λ_v=0.0833, λ_d=1.434	717.31 s	721.91 s
λ_v=0.0833, λ_d=1.792	727.39 s	733.80 s

policies after an exhaustive analysis of the their behavior in different scenarios and with different traffic profiles. Based on this characterization, heuristic policies were proposed and their performance was analyzed. We showed that they outperform the three fixed policies, particularly when the data arrival rate is larger than voice arrival rate. We also studied the optimization of the throughput considering QoS restrictions based on bounds on the blocking probabilities. The results showed that the advantages of the heuristic policies over the others are not affected by adding these constraints.

We introduced different types of vertical handoffs based on the previous analysis of the system. We determined and characterized new optimal policies according to the arrival type, system state and vertical handoff action. Since it is not computationally feasible to calculate the optimal policies through traditional policy iteration online, new heuristic policies with vertical handoffs were designed and evaluated. The evaluation of the new heuristic policies was done in a system larger than the one used to characterize the optimal policies from which the heuristic ones derive. However, we found that their performance scales very well with the cardinality of the state space, which is very close to the performance achieved by optimal policies.

We also analyzed the performance of these heuristic policies by simulation. We found that the simulation results practically overlap the analytical ones, which allowed us to validate the last ones. In addition to exponential distributions, we also evaluated the performance of the heuristic policies by simulation with the hyperexponential and Erlang distributions. An interesting and very important finding is that their performance is insensitive to distributions of the service time of the voice sessions and the elastic flow length (in bits) beyond the mean. The cost of vertical handoff was studied in relation to those of voice and data blocking, and some insightful remarks were done in order to understand the impact that vertical handoff has.

We have evaluated two approximated methods to solve a Markov decision process using the first step of policy iteration. The first method uses the embedded discrete time Markov chain to obtain the mean cost of the proposed initial policy of the system and this result is used to perform policy improvement. This method requires the definition of four parameters in order to obtain a required accuracy. The second method is based on the time scale separation assumption which states that due to the difference of time scales of data and voice events, it is possible to approximate the total system as two separate subsystems solved sequentially. In the first subsystem, data users see voice users as being still. In the second subsystem, data users influence is perceived by voice users affecting the arrival transition rates. The introduction of these conditional transition rates expands the reach of traditional time scale separation beyond the quasi-stationary and flow regimes solutions as boundaries. The mean cost obtained through this method is used to perform a single step of policy improvement as in the previous case, but setting only two parameters for accuracy.

The two solutions are compared against the optimal solution which was found using several steps of policy iteration based on the continuous time Markov chain of the system and solved through the LSQR algorithm. Results showed that the solutions obtained using the proposed methods are very close to the optimal solution for most scenarios, except when the arrival rate of voice calls is high. Also, it was shown that the two approaches introduced have a similar computational cost, and therefore its performance is almost identical, although the first one can use any initial policy and the second can only use initial policies that respect the time scale separation properties. Finally, it was shown that thanks to the computational cost reduction of the methods proposed, it is possible to perform more steps of policy iteration to obtain solutions that closely resemble the optimal in less time than the needed to perform a single step of policy iteration with LSQR.

The analysis of JCAC and JHC problems for heterogeneous systems in this chapter can be used to the analyze other RATs such as OFDMA, used in LTE or WiMAX, since the model is flexible in the definition of resources and user's requirements. This characteristic is a clear advantage for the analysis of multi RAT networks, since future analysis will require the coexistence of 4G networks with legacy technology. On the other hand, the two solution approaches of policy iteration can be useful to problems that can be analyzed through scale separation, since it has been shown that it is accurate and strongly reduces the computational cost. In particular, it can be applied to problems that include multiservice networks, due to the nature of voice and data calls.

Chapter 3

Admission control in cognitive radio networks

One of the most intuitive solutions for heterogeneous networks consists in improving the current macrocells. Proposed improvements include developing new antennas, the use of higher-order modulations, increasing sectorization, increasing the spectrum or using it more efficiently, among others. Spectrum efficiency has always been a main concern in wireless networks considering that it is a valuable and limited resource. However, a fixed assignment of large parts of the spectrum in extended geographical areas to licensed users has proven to be highly inefficient both temporally and spatially in dense and sparse cities [Com05] [Com07] [MTM$^+$06] [Uni12] . Cognitive Radio (CR) was proposed as a technology that would allow a dynamic spectrum access, which in the context of heterogeneous networks could imply e.g. spectrum sharing between operators or accessing underutilized spectrum such as that licensed to TV. The traditional concept of CR is to increase spectrum utilization by allowing CR users (or secondary users SU) to access the licensed wireless channel in an opportunistic manner so that interference to licensed users (or primary users PU) is kept to a minimum.

However, there are many challenges that have to addressed before CR networks become practically realizable [AGSA08], [ALVM08]. These can fit in one of the three main functions of CR: spectrum sensing, which is the ability to detect which part of the spectrum is available, power control, which controls the level of interference imposed over other users and the total capacity of the system and spectrum management, which allows a user to choose the most convenient part of the spectrum.

To fulfill the requirement of minimum interference to PUs, a SU with an ongoing session must vacate the channel when a licensed user is detected. To prevent the SU from dropping its ongoing session it may switch to a different unused spectrum band, which is referred to as spectrum mobility or spectrum handover (SH). If no available bands can be found or the SH procedure is not implemented, one o more SUs will be forced to terminate their sessions. The queuing literature studies about systems with two or more classes of customers where one has preemptive priority over the other, date back at least to the sixties, see [Jai68], [ZWdO09] and references therein. However, the topic is far from being closed and most, if not all, of the existing results assume that customer of all classes share the same service time distribution and/or each user consumes the same amount of resources regardless of its class. In general those assumptions are not suitable for CR systems since user type heterogeneity is an inherent characteristic of such systems. Furthermore, relaxing the homogeneity assumptions can render the model intractable [ZWdO09]. It is thus necessary to develop new simple models that help to gain an insight into the behavior of CR systems and serve as a first approximation to their design and configuration. Based on the obtained knowledge and experience more sophisticated and precise methods should be subsequently developed. On the other hand, a variety of studies that focus on priority mechanisms to handle conventional handovers in cellular networks have appeared in the literature, see [PCG05] and references therein. Notwithstanding, SH and conventional handover are different in nature and also from a modeling perspective. In this paper we focus on the study of the Quality of Service (QoS) seen by secondary users at the session level. As mentioned above, if a PU starts using a channel that is occupied by a SU the latter may be forced to terminate its ongoing sessions unless a SH to an unused channel is performed. From a user perspective, it is generally assumed that the interruption of an ongoing session is more annoying than denying initial access. Therefore, blocking the request of a new SU session, even if there are enough free channels, can be employed as a strategy to lessen the number of SU sessions forcefully terminated. By employing that approach a trade-off naturally arises between the probability of blocking and the probability of forced termination. Our purpose here is to gain insight into the effect that system parameters have on those two performance parameters of a CR network and, based on that, propose design criteria in order to balance adequately the conflicting requirements. We employ the same rather simple model than [ZSY07], which is enhanced to include an extension of the reservation scheme so that a non-integer number of channels can be reserved for SH. Such extension borrows the idea from the fractional guard channel scheme that was introduced in cellular networks [RNT97]. The greater flexibility of using a continuous configuration parameter instead of being constrained to a discrete one is expected to allow a more efficient use of resources. Furthermore, our numerical results for the system throughput are qualitatively different from those obtained in [ZSY07] leading to completely different conclusions, especially in what concerns the optimum system configuration. We propose two alternative configuration rules and show that, for both of them, an optimum value for the reservation parameter exists. These optimization criteria had already been employed in cellular networks to balance the trade-off that arises between blocking new sessions and handover requests [RNT97], [PCG03]. The content of this chapter has been published in [DVJ09] [JVD09] [JVMD10].

The rest of the chapter is organized as follows. In Section 3.1 we present the CR model of a system where SH with MFGC is implemented. In Section 3.2 we compare the throughput and forced termination probabilities of a system with and without SH and MFGC. An optimization function is used in Section 3.3, in order to reduce the blocking and forced termination probabilities of SU as a function of the guard channels for SH.Finally, Section 3.4

concludes this chapter.

3.1 System model

In this section we study a system that have a total of C RRUs, being the physical meaning of a unit of resource dependent on the specific technological implementation of the radio interface. It is assumed that a single service is provided. For the sake of mathematical tractability the common assumptions of Poisson arrival processes and exponentially distributed service times are used. The arrival rate for PU (SU) sessions to the system is λ_1 (λ_2), and a request consumes $b1$ ($b2$) resource units when accepted, $b_i \in \mathbb{N}, i = 1, 2$. For a packet based air interface, b_i represents the effective bandwidth of the session [BS97], [EE99]. We assume that $b_1 = N$, $b_2 = 1$ and that $C = M \times N$, therefore the system resources can be viewed as composed by $M = C/N$ bands for PUs or $M \times N$ sub-bands for SUs. The service time for primary and secondary sessions is denoted by μ_1 and μ_2 respectively.
We develop two analytical models to evaluate the performance of systems with and without spectral handover. We denote by $\mathbf{x} = (x_1, x_2)$ the system state vector, where there are x_1 ongoing sessions of PUs and x_2 of SUs. Let $b(\mathbf{x})$ represent the amount of occupied resources at state $\mathbf{x}$, $b(\mathbf{x}) = x_1 N + x_2$. The system evolution along time can be modeled as a multidimensional birth-and-death process. The set of feasible states for the process is

$$S := \{\mathbf{x} = (x_1, x_2) : x_1 N + x_2 \leq C\}.$$

3.1.1 System without spectral handover

A PU arrival in state x will force the termination of k SUs, $k = 0, \ldots, \min(x_2, N)$, with probability

$$p(\mathbf{x}, k) = \frac{\binom{N}{k}\binom{(M-x_1-1)N}{x_2-k}}{\binom{(M-x_1)N}{x_2}}$$

when k SUs are in the sub-bands occupied by the newly arrived PU session, while the other (x_2 - k) are distributed in the other $(M - x_1 - 1)$ sub-bands. Clearly,

$$\sum_{k=0}^{\min(x_2,N)} p(\mathbf{x}, k) = 1.$$

Let r_{xy} be the transition rate from $\mathbf{x}$ to $\mathbf{y}$, $x \in \boldsymbol{S}$, and be e_i a two dimensional vector with position i set to 1 and the other position set to 0, then

$$r_{xy} = \begin{cases} a_1(x)\lambda_1 & \text{if } y = x + e_1 - ke_2, \\ a_2(x)\lambda_2 & \text{if } y = x + e_2, \\ x_i\mu_i & \text{if } y = x - e_i, \\ 0 & \text{otherwise} \end{cases}$$

Note that $a_1(x) = p(x,k)$, if x+e_1-ke_2 $\in \boldsymbol{S}$, and 0 otherwise. Similarly, $a_2(x) = 1$, if x+e_2 $\in \boldsymbol{S}$, and 0 otherwise. Figure 3.1 shows the state diagram and transition rates of the continuous-time Markov chain (CTMC) that models the system dynamics. The global balance equations can be expressed as

$$\pi(\mathbf{x}) \sum_{\mathbf{y} \in S} r_{\mathbf{xy}} = \sum_{\mathbf{y} \in S} \pi(\mathbf{y}) r_{\mathbf{xy}} \;\; \forall \;\; \mathbf{x} \in \boldsymbol{S} \tag{3.1}$$

where $\pi(\mathbf{x})$ is the state $\mathbf{x}$ stationary probability. The values of $\pi(\mathbf{x})$ are obtained from (1) and the normalization equation. From the values of $\pi(\mathbf{x})$ the blocking probability for SUs requests P_2 and their forced termination probability P_2^{ft} can be determined. Let us define

$$k(\mathbf{x}) = \sum_{\beta=0}^{\min(x_2,N)} \beta p(\mathbf{x}, r)$$

then,

$$P_2 = \sum_{\mathbf{x} \in S} (1 - a_2(\mathbf{x}))\pi(\mathbf{x}) \tag{3.2}$$

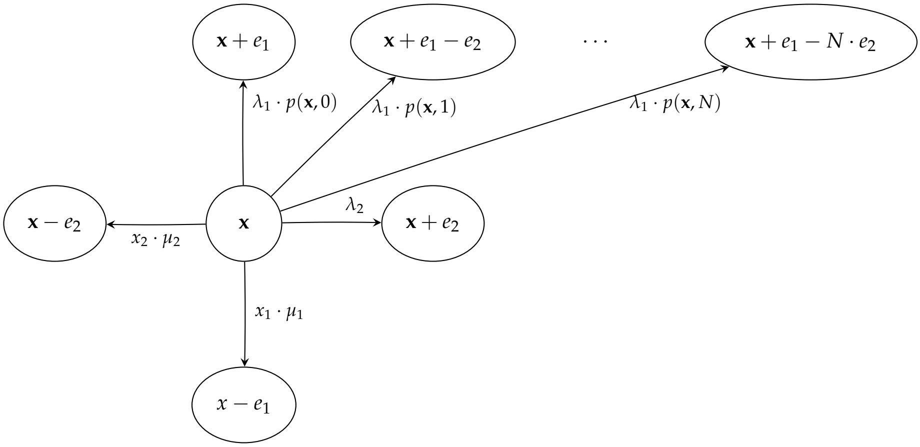


Figure 3.1: Transitions for system without spectral handover.

and

$$P_2^{ft} = \frac{\sum_{\mathbf{x}\in S} k(\mathbf{x})\pi(\mathbf{x})\lambda_1}{\lambda_2(1-P_2)}. \tag{3.3}$$

Finally, the throughput of SUs, i.e. the successful completion rate of SUs is determined by

$$Th_2 = \lambda_2(1-P_2)(1-P_2^{ft}). \tag{3.4}$$

3.1.2 System with spectral handover

It is usually accepted that it is more disturbing for a subscriber in a cellular network to have an ongoing session dropped than the blocking of a new session setup. Then, to guarantee a certain degree of QoS to the SUs, we deploy the fractional guard channel (FGC) admission policy. When a SU new setup request arrives to the system, an admission decision is taken according to the number of free resource units:

$$C - b(\mathbf{x} + e_2) = \begin{cases} > \lfloor t \rfloor & \text{accept} \\ = \lfloor t \rfloor & \text{reject with probability } \; t - \lfloor t \rfloor \\ < \lfloor t \rfloor & \text{reject} \end{cases}$$

where we denoted by $t \in$ [0, C], the admission control threshold, i.e. the average number of resource units that must remain free after accepting a new requests of SUs is t. Clearly, these resources are reserved for SUs performing spectral handovers. Then, the higher the t the lower the forced termination but the higher the blocking probability perceived by the new requests and vice versa. Note also that the PUs are unaffected by the admission policy, as SUs are transparent to them.
A PU arrival in state $\mathbf{x}$ will not force the termination of SUs when the system state complies with $C - b(\mathbf{x}) \geq N$, as the execution of spectral handover will allow to find new unused sub-bands. On the other hand, when $C - b(\mathbf{x}) < N$, $x_1 < M$, a PU arrival will preempt $b(\mathbf{x} + e_1) - C$ SUs. Let $k(\mathbf{x})$ be the number of preemptions in state $\mathbf{x}$, then

$$k(\mathbf{x}) = \begin{cases} b(\mathbf{x} + \mathbf{e}_1) - C & \text{if } C - b(\mathbf{x}) < N, x_1 < M, \\ 0 & \text{otherwise} \end{cases}$$

As before, let $r_{\mathbf{xy}}$ be the transition rate from $\mathbf{x}$ to $\mathbf{y}$, $\mathbf{x} \in \mathbf{S}$, then

$$r_{\mathbf{xy}} = \begin{cases} a_1(\mathbf{x})\lambda_1 & \text{if } \mathbf{y} = \mathbf{x} + \mathbf{e}_1 - k(\mathbf{x})\mathbf{e}_2, \\ a_2(\mathbf{x})\lambda_2 & \text{if } \mathbf{y} = \mathbf{x} + \mathbf{e}_2, \\ x_i\mu_i & \text{if } \mathbf{y} = \mathbf{x} - \mathbf{e}_i, \\ 0 & \text{otherwise} \end{cases}$$

The coefficients $a_1(\mathbf{x})$ and $a_2(\mathbf{x})$ denote the probabilities of accepting a PU arrival and a SU arrival, respectively. It is clear that $a_1(\mathbf{x}) = 1$, if $\mathbf{x} + \mathbf{e}_1 - k(\mathbf{x})\ \mathbf{e}_2 \in S$, and 0 otherwise. Given a policy setting t, $a_2^n(\mathbf{x})$ is determined as

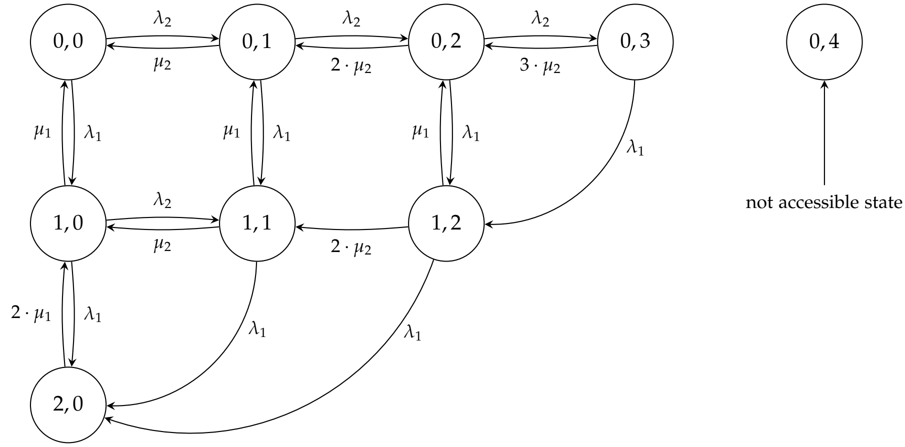


Figure 3.2: System with SH, M=2, N=2, t=1

follows

$$a_2(\mathbf{x}) = \begin{cases} 1 & \text{if } C - b(\mathbf{x} + \mathbf{e}_2) > \lfloor t \rfloor, \\ 1 - (t - \lfloor t \rfloor) & \text{if } C - b(\mathbf{x} + \mathbf{e}_2) = \lfloor t \rfloor, \\ 0 & \text{otherwise} \end{cases}$$

The parameter t restricts the acceptance of secondary users, and therefore has an impact in the state space S as defined earlier. In Figs 3.2 and 3.3, the Markov process for two systems with integer and fractional guard channels, are shown. It can be seen that state $\mathbf{x}$ =(0,4) is not accessible since a guard channel condition applies. However, this condition is not the only necessary condition for a state to be inaccessible, since state $\mathbf{x}$=(1,2) is also affected by the guard channel condition, but it can be accessed by the arrival of primary users through $\mathbf{x}$=(0,2) and $\mathbf{x}$=(0,3).

By solving the global balance equations (3.1), together with the normalization equation, the values of $\pi(\mathbf{x})$ can be obtained, and from them the blocking probability for SUs requests P_2, their forced termination probability P_2^{ft} and the SUs throughput Th_2 can be determined using (3.2), (3.3) and (3.4).

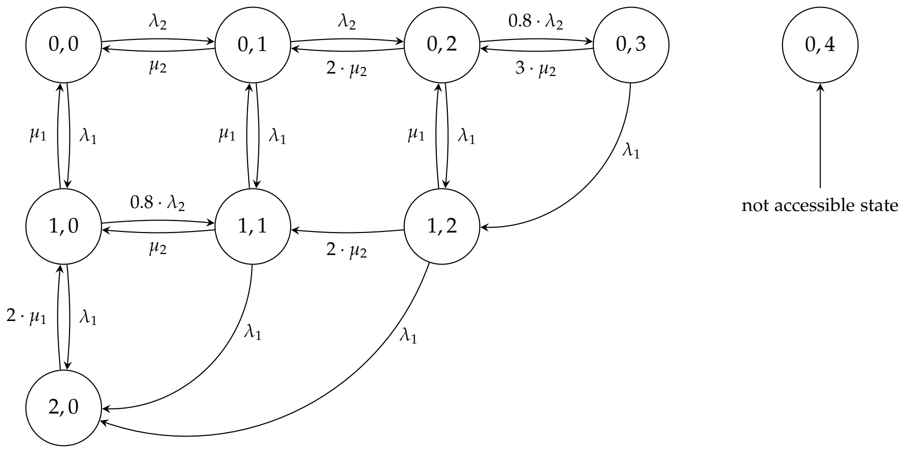


Figure 3.3: System with SH, M=2, N=2, t=1.2

3.2 Throughput and forced termination probability of secondary users

In this section the performance of a system with spectral handover and another without it are evaluated. The reference scenario is described in Table 3.1. Figures 3.4 and 3.5 show the throughput of SUs as a function of the arrival rate of primary and SUs respectively. For each of the two figures we also show the impact of reservation. Figure 3.6 shows the results obtained by simulating the system physical behavior. Note the excellent agreement between the analytical and simulation models. Although almost imperceptible, note also that confidence intervals for a confidence level of 95% have been depicted in the figure. The load region for the study in Fig. 3.4 has been chosen such that the traffic offered by PUs expressed in sub-bands varies from 0 to 16 Er., while the offered by SUs is 0.83 Er. On the other hand in Fig. 3.5 the traffic offered by SUs expressed in sub-bands varies from 0 to 19.51 Er., while the offered by PUs is 8 Er.

Table 3.1: Scenario Description

System	Clients
M=3	λ_1=0.08
N=6	λ_2=0.68
C=18	μ_1=0.06
	μ_2=0.82

The authors of [ZSY07] suggest that a natural way of configuring a cognitive radio system of similar characteristics is to choose t for each arrival rate of SUs such that their throughput is maximized. As observed in previous figures, it is not possible to determine an optimum operating point beyond the obvious one that is to deploy spectral handover and $t = 0$. The results confirm the intuition that increasing t beyond $t = 0$ to maximize the throughput has no sense. Guard channels have been classically deployed in cellular systems to limit the forced termination of accepted sessions and we believe that their role in cognitive radio systems is the same. Therefore the number of guard channels cannot be chosen to maximize the throughput of SUs. Clearly, the higher the number of guard channels the lower the forced termination probability but the higher the blocking probability of new requests, which might reduce the system revenue. In the following sections we explore alternative ways to perform the system configuration that take this trade-off into consideration.

On the most interesting results of the cognitive radio system studied is the evolution of the forced termination with the arrival rate of SUs shown in Fig. 3.7. Observe that it seems to have a counter-intuitive behavior. Intuitively, one would expect that the forced termination would increase with the arrival rate of SUs. However in a system without spectral handover it has the opposite behavior. Note also that in a system with reservation and particularly for some reservation values like $t = 3$ or 4, the forced termination first decreases, attaining a minimum, and then increases. These phenomena

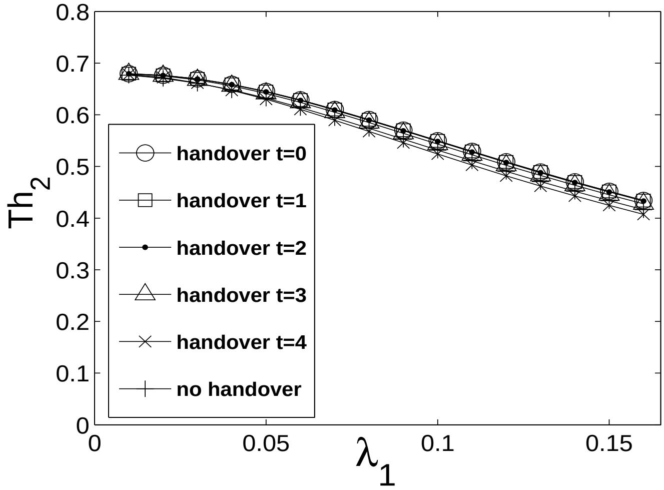


Figure 3.4: Throughput with the arrival rate of primary users.

can be explained as follows. As in the scenario of Fig. 3.7 the arrival rate of PUs is constant, then P_2^{ft} depends only on the ratio of forced terminations to accepted sessions. For a system without spectral handover, if we compare the evolution of the forced termination rate with the acceptance rate for the interval of arrival rates of interest, it is clear that the acceptance rate grows more quickly than the forced termination rate in the first half of the interval, while both rates tend to grow with a similar slope by the end of the second half of the interval.

In other words, from the point of view of the acceptance rate, the first part of the interval is dominated by an almost blocking free behavior and therefore it grows almost linearly with the arrival rate. In the second half the blocking starts to grow and the acceptance rate tends to stabilize by the end of the interval. This behavior is alike the one in Erlang systems, where the carried traffic increases linearly with the arrival rate up to a point beyond which it tends asymptotically to the system capacity. When the system does support spectral handovers and the SUs arrival rate is low, most of the users

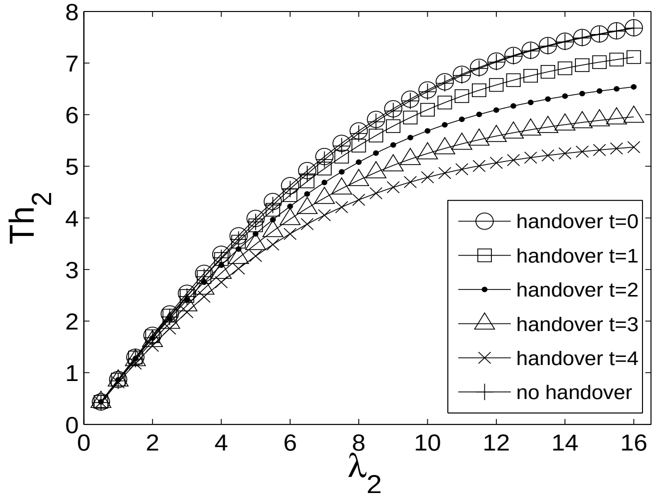


Figure 3.5: Throughput with the arrival rate of secondary users.

are accepted in the system and the forced terminations are almost nonexistent. As the arrival rate increases, the number of unsuccessful spectral handovers start to grow or equivalently the number of forced terminations start to grow. This point can be identified in Fig. 3.7 as the one where the negative slope of P_2^{ft} starts to decrease. As the arrival rate keeps on increasing, the slope of the acceptance rate starts to decrease while forced termination rate is maintained. This causes the slope of P_2^{ft} to change sign and to start growing on the positive side. Note that this behavior is magnified when the system deploys reservation.

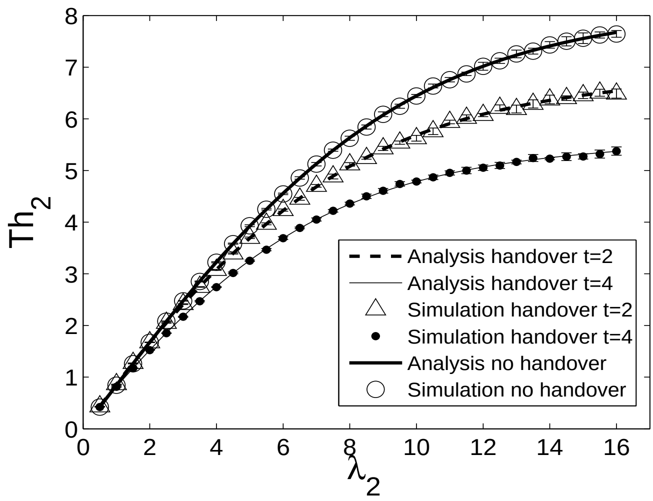


Figure 3.6: Comparison of results from the analytical and simulation models.

3.3 Parameter optimization

3.3.1 System configuration by minimizing a cost function

We define the cost function

$$\gamma = P_2^n + \beta P_2^{ft}$$

where β allows the operator to weight adequately the cost of forced terminations against the cost of blocking SUs, i.e. a forced termination is β times more costly than a blocking. Our objective is to determine the value of t that minimizes γ.

For the reference scenario defined in Table 3.1, Fig. 3.8 shows the optimum value of t as a function of the arrival rate of PUs for different values of β. For the load region of study, the optimum t takes values in the multiples of N. Ramjee et al. showed in [RNT97] that in a cellular system with two arrival types, new and handovers, the optimal policy is of the guard channel

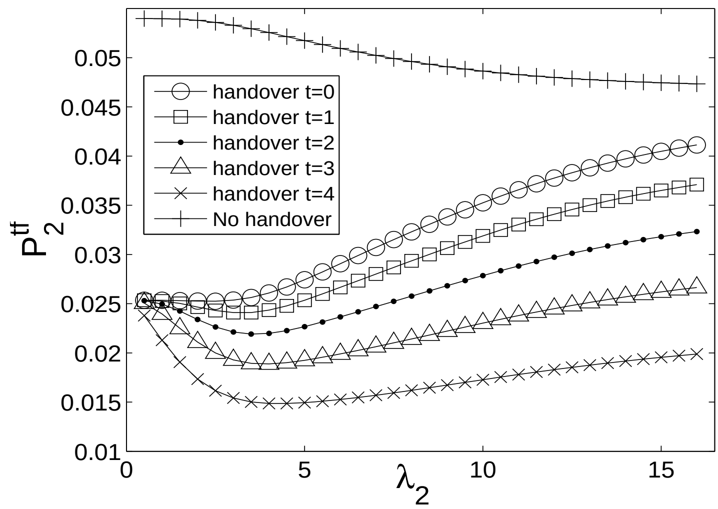


Figure 3.7: Forced termination with the arrival rate of secondary users.

type when the problem is formulated as the unconstrained minimization of a cost function that is a linear combination of the blocking probabilities for new and handover arrivals. In other words, the optimal policy is of the threshold type, where states for which the number of free resource units is higher than the threshold have associated acceptance actions, when it is equal or lower than the threshold have associated rejection actions and the threshold is a positive integer. Note that our context is completely different to the one studied in [RNT97]. In our system, the mean service times and the number of resources occupied by the sessions of the two arrival streams are different. Nevertheless, our results show an empirical evidence that the conclusions of [RNT97] might be also applicable here. Then, for the load region of interest when the primary arrivals consume N resource units, reserving non multiples of N resource units for secondary arrivals clearly has no impact. This phenomenon needs further investigation.

Figure 3.9 shows the variation of the optimum t as a function of the arrival rate of PUs for different values of N and when $\beta = 20$. As observed, the

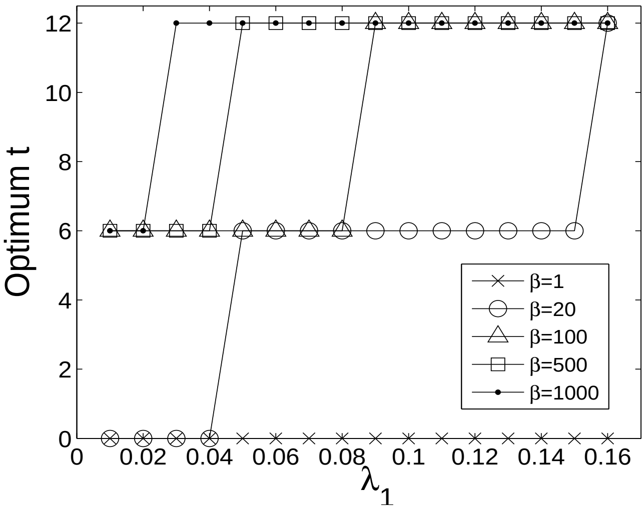


Figure 3.8: Optimum t as a function of the arrival rate of primary users.

optimum reservation pattern follows the same rule given before.

Figure 3.10, Fig. 3.11 and Fig. 3.12 show, respectively, the throughput, blocking probability and probability of forced termination for SUs as a function of the arrival rate of PUs for different values of N when $\beta = 20$. Note that for each value of λ_1 and N the optimum t is deployed and that discontinuities are clearly visible when the value of t changes. Observe also that SUs performance parameters are almost unaffected by the value of N. When performing a zoom of some parts of the figures, one observes differences in the fourth or fifth decimal which are clearly negligible.

Figure 3.13 displays the optimum value of t as a function of the arrival rate of SUs for different values of β. Note that depending on the value of β now the optimum t is not a multiple of N and that, as in Fig. 3.8, the bigger the β the more costly are the forced terminations, and therefore the higher the amount of resource units the system reserves to prevent this from occurring. Note also that for $\beta = 20$ and $\beta = 30$ the optimum t has a counter-intuitive behavior as it decreases when λ_2 increases and then, as λ_2 increases further,

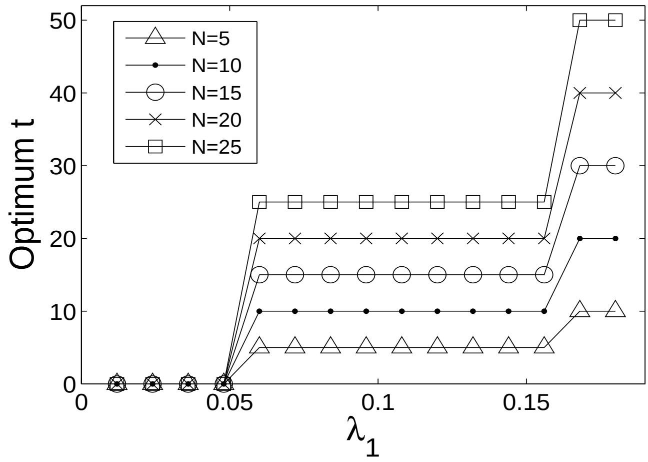


Figure 3.9: Optimum t for different values of the number of sub-bands N required to a carry a primary user session.

t increases. This is due to the non-monotonic shape of the cost function γ in the load region of study, but it requires more investigation to understand the intuition of the behavior.

3.3.2 System configuration by bounding the forced termination probability

We explore now the optimal configuration of t when the QoS objective is to guarantee a given bound for the forced termination probability of SUs. In this case, we intend to determine the value of t that minimizes the blocking probability of SUs, while guaranteeing a bound for their forced termination probability.

Figure 3.14 displays the optimum value of t as a function of the arrival rate of PUs for different bounds for the forced termination probability. Note

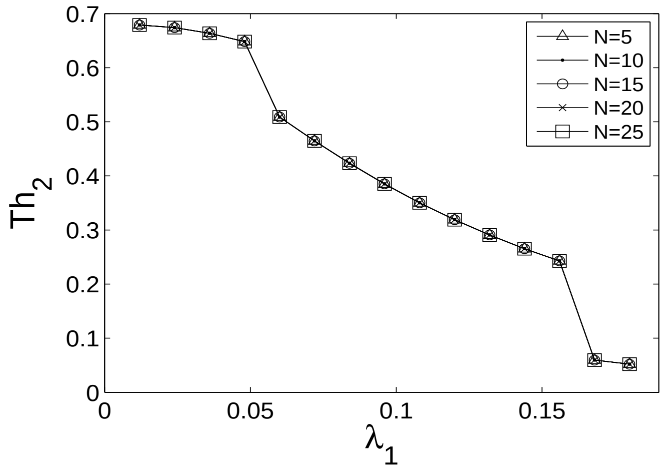


Figure 3.10: Throughput when deploying the optimum t.

that t takes now real values. Ramjee et al. showed in [RNT97] that in a cellular system with two arrival types, new and handovers, the optimal policy is of the fractional guard channel type when the problem is formulated as the minimization of the blocking probability of new requests subjected to a constraint on the handover blocking probability. In other words, the optimal policy is of the threshold type, where states for which the number of free resource units is greater than $\lfloor t \rfloor$ have associated acceptance actions, when it is smaller than $\lfloor t \rfloor$ have associated rejection actions, when it is equal to $\lfloor t \rfloor$ have associated a randomized rejection action, and the threshold is a positive real. As stated in previous Section, note that our context is completely different to the one studied in [RNT97] and, therefore, our results show an empirical evidence that the conclusions of [RNT97] might be also applicable here. A more general result was obtained by Ross in [Ros89], that showed that for the Markov decision problem of determining a policy to minimize the infinite-horizon average cost subject to K infinite-horizon average cost constraints in unichain systems, there exists an optimal solution with a degree of random-

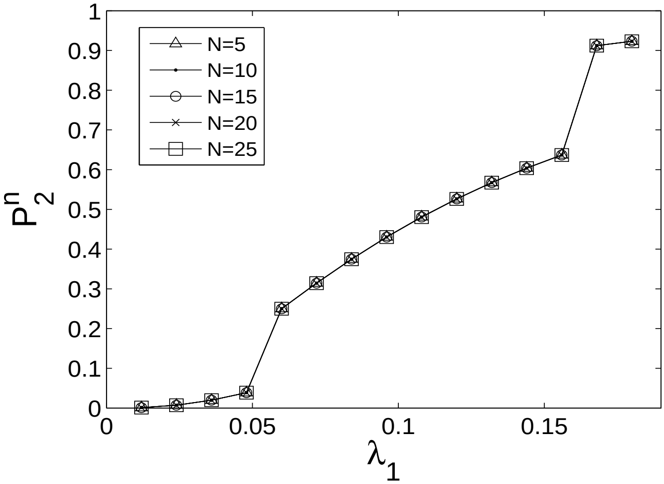


Figure 3.11: Blocking probability when deploying the optimum t.

ization no greater than K, i.e. it is never necessary to randomize in more than K states.

By maintaining constant the arrival rate of SUs, Fig. 3.15 shows a similar reservation pattern to the one shown in the scenarios studied in Section 3.3.1, i.e. the system tends to reserve resources in the multiples of N, but while previously the optimum t displayed a step-wise shape, now the approximation to the multiples of N happens progressively as λ_1 grows.

As in the previous Section, Fig. 3.16, Fig. 3.17 and Fig. 3.18 show, respectively, the throughput, blocking probability and probability of forced termination for SUs as a function of the arrival rate of PUs for different values of N. Recall that for each value of λ_1 and N the optimum t is deployed. The most notorious fact is that SUs performance parameters are unaffected by the value of N. This means that for each value of N, it is possible to find a value of t that can maintain the performance of the system. Also, it is worth to mention that the constraint $P_2^{ft} \leq 0.02$ is always met.

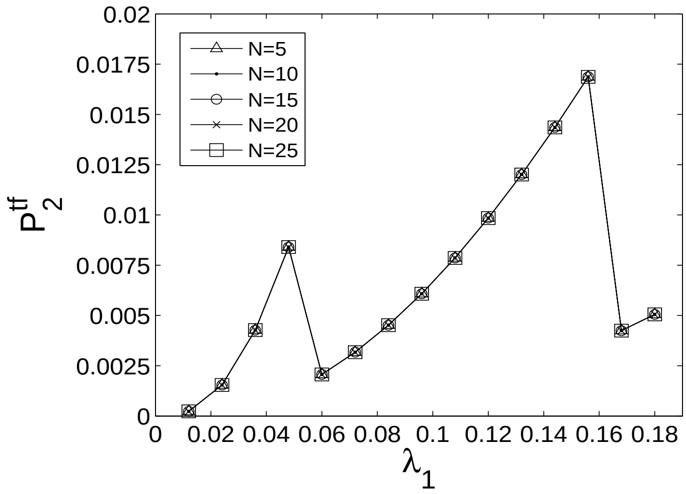


Figure 3.12: Forced termination probability when deploying the optimum t.

3.4 Conclusions

In this chapter we have studied a cognitive radio system in which SUs vacate a channel due to a primary user arrival using spectrum handover. In order to limit the forced termination probability of SUs a fractional guard channel reservation scheme is applied to give priority to spectrum handovers over new arrivals.

A previous study showed that, for each system load, the number of guard channels could be configured to maximize the throughput of SUs in systems with spectral handover. We provide sufficient evidences that this approach does not achieve the intended objective. Even further, we believe that the role of guard channels in cognitive radio systems is the same as their classical role in cellular systems, i.e. to limit the forced termination probability of SUs.

Clearly there exits a trade-off between the forced termination probability and the blocking probability, i.e. the higher the number of guard channels the lower the forced termination probability but the higher the blocking proba-

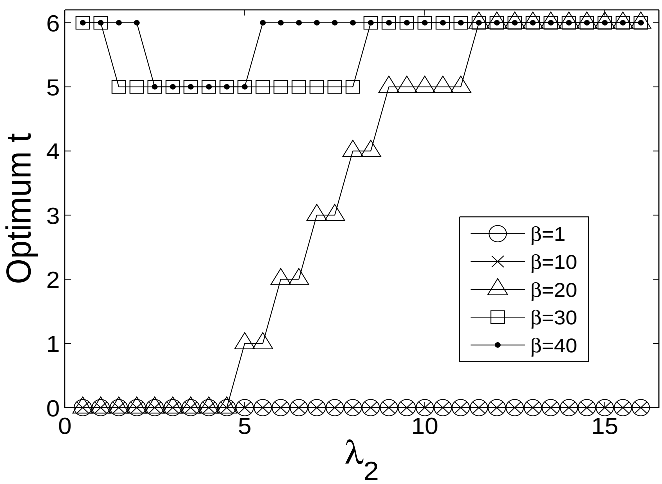


Figure 3.13: Optimum t as a function of the arrival rate of secondary users.

bility of new requests, which might reduce the system revenue. Therefore, we propose and explore two ways of determining the optimum number of guard channels. In the first approach the objective is to minimize a cost function which is a linear function of the blocking and forced termination probabilities. An important characteristic of the optimal solutions is that they tend to use an integer number of guard channels. In the second approach the objective is to minimize the blocking probability subject to a constraint in the forced termination probability. This is done since the forced termination probability is considered more harmful.

The results obtained in this chapter provide an effective analysis on the effect that guard channels has over the throughput, which is significant given the importance that spectrum handover has in spectrum management studies. These results allow the analysis of QoS provision, which is a fundamental feature of any competitive wireless technology. A future line of work is to obtain optimal solutions using dynamic programming methods, that could increase the knowledge over channel reservation.

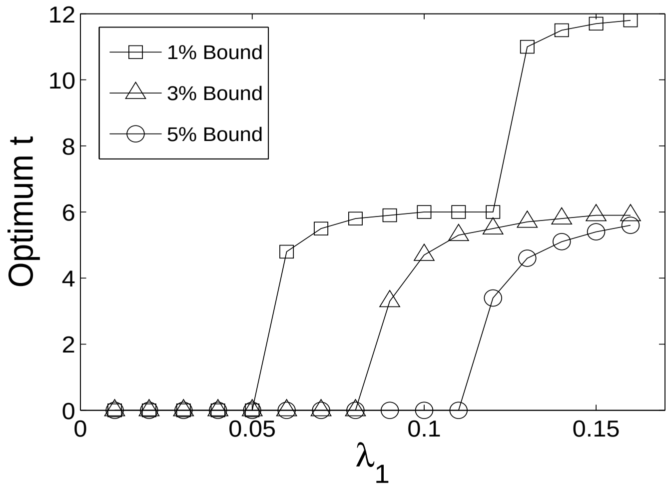


Figure 3.14: Optimum t as a function of the arrival rate of primary users.

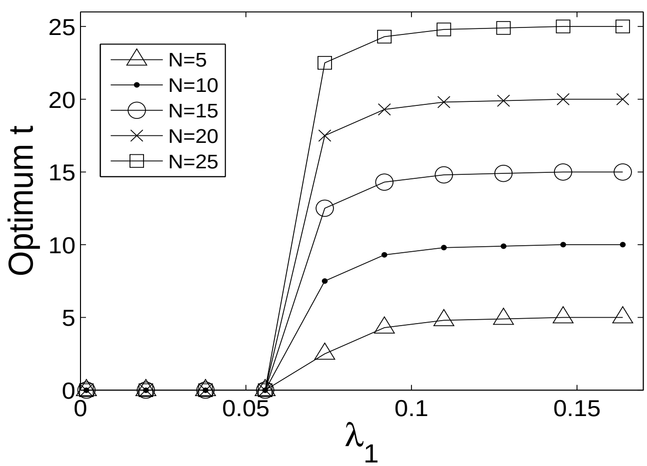


Figure 3.15: Optimum t for different values of the number of sub-bands required to a carry a primary user session N.

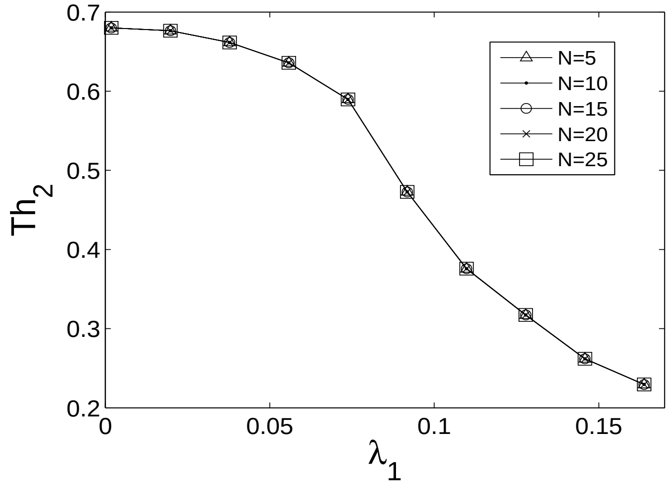


Figure 3.16: Throughput when deploying the optimum t.

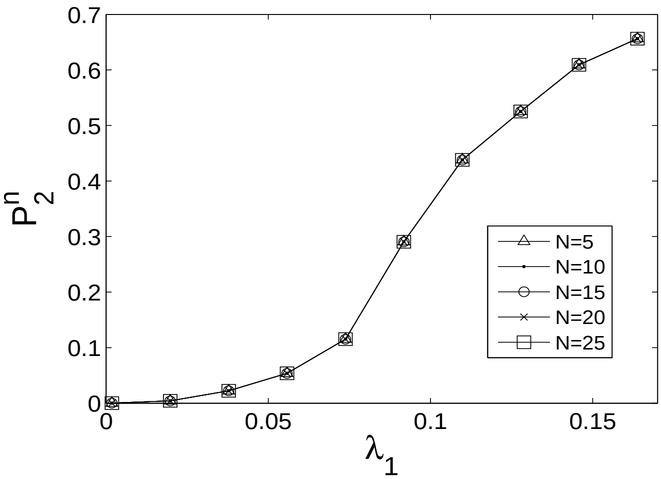


Figure 3.17: Blocking probability when deploying the optimum t.

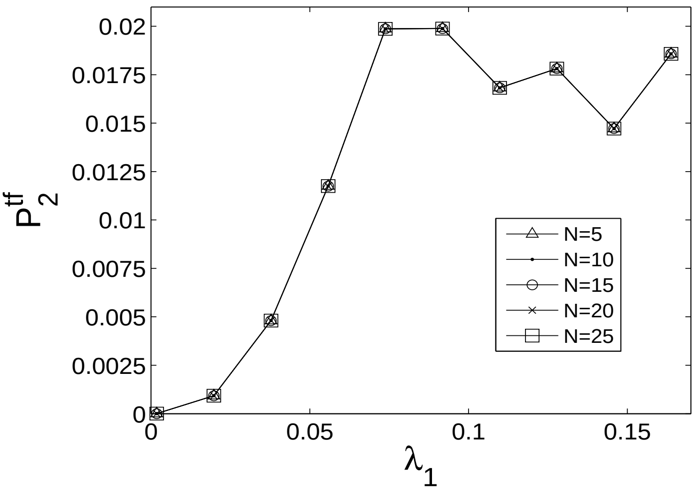


Figure 3.18: Forced termination probability when deploying the optimum t.

Chapter 4

Signaling overhead for location update procedures in small cell networks

Although multi-layered mobile networks are not new, in the context of heterogeneous networks they play a crucial role in order to be able to fulfill the capacity requirements that are being imposed by data growth. In particular, small cells are aimed to support the increase of indoor traffic that according to [ff10] represents over 80% of the total data traffic. The main characteristic of this new generation of small cells is that although it makes use of the licensed spectrum it has an IP-based backhaul which makes them considerably cheaper, and therefore more attractive for providers. This characteristics bring new issues that must be considered in order to integrate small cells into the existing mobile networks.

Arguably, the most studied subject in small cells is interference. However, the focus of this chapter is in mobility, and specifically in location management. As it is known, small cells have a limited backhaul, and its capacity may be shared with a wired user. Considering that mobility involves significant signaling, backhaul capacity limitations cannot be ignored. On the other hand, smaller coverage areas imply that users may cross cells more often, increasing the signaling load and raising the requirements on latency. This is very important since 3GPP mobility procedures assume a direct connection to the core network that does not exist for this type of cells.

In this chapter we focus in the signaling load of location management procedures for small cell networks. This procedures are implemented to keep track of user's location in idle mode through two functions: Location Update (LU) and paging. The former is performed by a User Equipment (UE) to inform about its current position to the network. The latter is performed by the network to locate the user among the cells in the network. Hence, increasing LUs reduces the amount of needed paging, and increasing paging reduces the amount of LUs. The optimal trade-off between the frequency of LUs and the amount of cells paged has been extensively studied in cellular networks [AHL96], [CGMO98].

The location management standardized by 3GPP is based on three components: cell, Tracking Area (TA), and the Tracking Area List (TAL). A cell is the minimum unit of coverage for UEs, A TA is a group of cells with a common identifier, where each cell belongs to only one TA. A TAL is a per-user-defined set of TAs where each particular user can move without performing an LU. If the user moves into a TA that is not in its TAL then it performs an LU to inform about its position to the Mobility Management Entity (MME), an element that belongs to the core network. After an LU is received, the MME keeps track of the user location and sets a new TAL for the user. Therefore, the frequency of LUs is reduced as the size of the TAL increases. In terms of paging, this means that the network knows each user location with a per-TAL granularity, which sets a bound to the maximum number of cells paged.

Since the amount of LUs increase due to the reduced coverage areas, in [FMB12] the TAL size is dynamically changed according to the users' speed. However, this solution has a high cost since it requires the introduction of specific timers for each user in the MME. Also, backhaul capacity limitations set tighter restrictions on the signaling load. Signaling reduction can be achieved through a careful TAL design, by considering UEs profiles. Yet, performance depends on having the correct information of the network, which is not always possible [RYGM10]. Large deployments of SCs produce large signaling loads in the core network, and in this particular case in the MME. A reduction in MME signaling can be achieved by using the X2 interface. This interface has been defined in 3GPP to support a direct interaction among cells even in the absence of a direct physical connection. Most of the available functions through this interface do not need the supervision of the core network (energy saving, radio link failure messages) [3GP12b]. Other functions reduce the load in the core network (mobility management in connected mode). Although location management functions are not defined for this interface, a paging procedure through the X2 interface is proposed in [FMBNMZ12]. This is very useful since small cell deployments are not always covered by a macro-cell and therefore some independence is expected. However, this paging procedure is done by routing through one-hop steps, which increases the load in the backhaul for large deployments.

In this chapter, to reduce the signaling associated to paging we define a Local Anchor (LA) that will register the current user position in terms of SC or TA. LA-based solutions have already been proposed to reduce signaling in cellular networks by choosing a VLR as LA [HA96]. Nevertheless, in our solution the LA is chosen from all the SCs in the TAL in a per-user-basis, thus distributing the processing load. Also, the communication from each SC to the LA is done through the X2 interface, which reduces the load in the MME. For scalability purposes we use an X2-Gateway (X2-GW) [3GP12a], so each SC maintains a single X2 connection. In addition to scalability issues, the X2-GW is used to provide X2 connectivity between SC and macrocells, thus allowing cooperation among macrocells and SCs. Through a Markov model with aggregated states we calculate the mean number of signaling for LU and paging obtained with our proposed solutions and a 3GPP-based scheme. Then, we evaluate the mean cost of each of these schemes. Finally, we show that it is possible to set the size of the TAL for the X2-Interface-based solutions to obtain a better performance than the 3GPP-based scheme.

The rest of the chapter is organized as follows. In Section 4.1 we review the 3GPP solution for location management and propose two local anchor based solutions. In Section 4.2 we present the model of the small cell deployment, as well as the mobility model. Also, we present the main parameters used to analyze the solutions and their definition. Then, in Section 4.3 we present the costs associated to LU and paging as a function of the parameters solved in the previous Section. Final remarks of this chapter are presented in Section 4.5

4.1 Location update procedures in small cells networks

4.1.1 3GPP-based location update scheme

The general scheme of the location update and paging procedures as defined by 3GPP is shown in Fig.1. SCs are assigned to TAs and a user can identify the TA of its current SC through a unique identifier, the Tracking Area Identity (TAI). TAs are also grouped into Tracking Area Lists (TAL). A TAL is a set of TAs where UE can move without performing LUs. TALs are defined in a per-user basis, and managed by the MME, the element in the core network that controls all mobility issues. In Fig. 4.1, a deployment of 7 SCs is shown, where each of them belongs to one out of three TAs. The correspondence of SCs and TAs is as follows: TA 1={SC 1,SC 2}, TA 2={SC 3,SC 4,SC 5} and TA 3={SC 6,SC 7}. An important characteristic of TALs is that two or more TALs can overlap to reduce the ping-pong effect. Since the standard does not specify how TALs are constructed, throughout this work we use overlapping TALs, i.e., neighbor TALs will share the border TA. Therefore, in Fig. 4.1, TA 2 belongs to both TAL x and TAL y.

Let us consider a UE who moves from SC 1 to SC 6 following the route *A*-*B*-*C*. This user originally belongs to TAL x. In transition *C*, SC 6 broadcasts its TAI. When the UE receives the TAI that does not belong to its TAL performs a location update (LU). This process has a twofold purpose: First, it informs the network of the user equipment (UE) location. Second, it informs

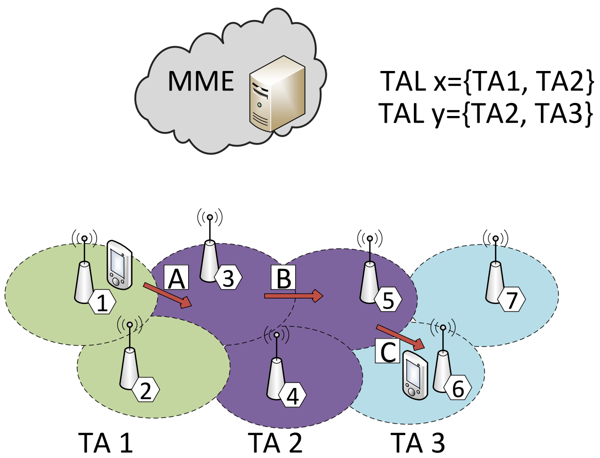


Figure 4.1: Core Network Architecture, and LU and Paging in 3GPP

the UE of the new TAL where it belongs, in this case TAL y. This means that the paging procedure is done on a TAL-basis. For example, if a user is following the same route *A*-*B*-*C*, and a call arrives just after location *B*, the MME only knows that the user is inside TAL 1, and will page accordingly to that information. Since the paging procedure is not defined by the standard, the 3GPP scheme proposed uses a sequential scheme that pages the last registered cell, then the last registered TA and finally the whole TAL. This simple scheme reduces the signaling associated to paging, as it is shown in [LL12].

4.1.2 X2-Interface-Based location update scheme

We propose to use location management functions through the X2-Interface to reduce the total signaling cost of the 3GPP-based scheme. In Fig. 4.2, the same SC deployment of Fig. 4.1 is shown, but in this case each SC has a X2 connection to the X2-GW. This element is responsible for maintaining the X2 connections among SCs. It is placed in the HeNB-Gateway [3GP12a], which is the entity in charge of connecting several SCs to the Core Network (CN). This is convenient for scalability purposes and to allow X2 connectivity to macrocells. In this case, as a UE enters the ECM-idle mode, which means that the user is registered to the network but is not active, it registers its position to the MME, receives a TAL from the MME and registers its position to the Local Anchor (LA). Any SC can be a local anchor, and this element is responsible for keeping track of its registered UEs. Additionally, the local anchor is defined on a per-user basis, which allows to distribute the signaling load among all the SCs in the TAL.

In the first proposed scheme, a user will send LUs to the LA through the X2 interface in a SC-basis. Therefore,each time a user hops from one SC to another, an intra-TAL LU message is sent to the LA, which will keep a record of the last visited cell. In Fig. 4.2 a UE is originally placed in SC 1 and follows the route *A*-*B*-*C*. Since SC 1 is the first SC where the UE is registered, it is chosen as its LA. The UE sends a message to SC 1 just after *A* and *B*, and then it sends a message to the MME in *C*, where SC 6 is chosen as the new LA. If the UE receives a call just after *B*, the LA receives the paging message, and forwards it to the current SC (SC 5) through the X2-GW. Therefore, this scheme has the minimum granularity.

In the second proposed scheme, a user will send LUs to the LA through the X2 interface in a TA-basis. In this case, when the user hops from one TA to another, an intra-TAL LU message indicating the new TAI is sent to the LA. Let us consider a UE originally placed in SC 1 that follows the route *A*-*B*-*C* as shown in Fig. 4.2. The chosen LA is the same as in the previous scheme. However, it only sends a LU to the LA in *A*, and then in *C* sends a LU to the MME. If the user is forwarded a call after *B*, the LA will only know its current TA, and therefore all the SCs inside TA 2 will be forwarded the paging message through the X2-GW. After leaving the former TAL, the user has to change the LA to the first visited cell in the new TAL.

Let us recall that both schemes are compliant with the 3GPP standard, since LU messages are still sent to the core network when the UE leaves a

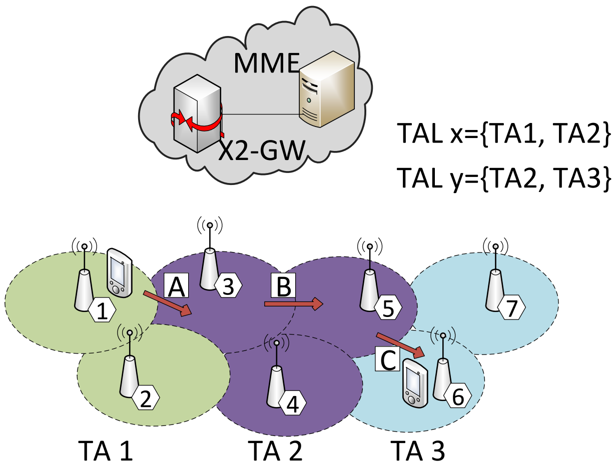


Figure 4.2: Core Network architecture, and LU and Paging in X2-Interface-Based Schemes.

TAL. The main objective of this feature is to reduce the paging overload that is expected from large deployments of SC by reducing the granularity of the UE location.

4.2 Analytical model

Let us consider a large deployment of SCs covering square areas as shown in Fig. 4.3. Each TA is composed by NxN small cells. In the same way each TAL is composed by VxH TAs. To reduce the ping-pong effect, TALs overlap. Let us define that TAL 1 as composed of {TA 4,TA 5,TA 8,TA 9}, and surrounded by the black line in Fig. 4.3. TAL 2 is composed of {TA 5,TA 6,TA 9,TA 10}, and surrounded by the blue line. If a UE registered in TAL 1 and staying in TA 5 moves to TA 6, its TAL will change from TAL 1 to TAL 2. If the user goes back from TA 6 to TA 5, the UE remains in TAL 2, since the TALs

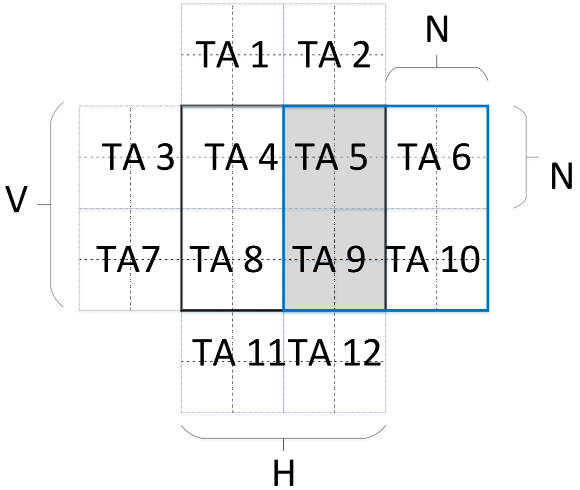


Figure 4.3: Overlapped TAL 1 and TAL 2, N=2, V=2, H=2.

overlap and TA 5 belongs to both TAL 1 and TAL 2.

We assume that a UE has the same probability of going in each of its four possible directions at any given time (random-walk model). Based on these characteristics, we can obtain the necessary parameters to calculate the cost of each solution,namely, The mean number of TAL updates after k movements $\overline{TAL}_c^k$, the mean number of TA updates after k movements $\overline{TA}_c^k$, the probability of ending in the same SC after k movements p_{SC}^k, and the probability of ending in the same TA after k movements p_{TA}^k.

4.2.1 Mean number of TAL updates after k movements

We study the dynamics of the system only by considering the SCs inside a single TAL and their adjacent SCs in the neighboring TALs. This is possible because after a UE visits a SC outside the TAL, the stochastic model of its dynamics will replicate identically in a new TAL. As a consequence we describe the stochastic model of the UE dynamics through a discrete-time

Markov chain of NxNxHxV states for the intra-TAL + 2xNxV+2xNxH states for the adjacent states. In Fig. 4.4(a), we show the diagram of the 16 SCs that belong to the TAL described at the beginning of this section, and its 16 adjacent SCs. In order to simplify the calculations, we use an aggregated method, partially based on [KS04], which considers the symmetry of the cells in terms of probabilities of leaving its TA and TAL. The aggregated diagram is shown in Fig. 4.4(b). Clearly, the probabilities for a UE located in the SC 4, SC 7, SC 10, and SC 13 in Fig. 4.4(a) of leaving its TA and TAL are the same, and that is why they all belong to aggregated state 1 on Fig. 4.4(b). The same reasoning can be applied for the aggregated states 2 and 3. Let us now consider the diagram of Fig. 4.4(b) in the case where a UE enters SC 18 through SC 2. According to the fact that the TALs overlap, as shown in Fig. 4.3, the position that this UE will occupy in its new TAL will be that of SC 4 in the old TAL. Hence, state 18 behaves like state 4. However, under the aggregation diagram in Fig. 4.4(b), state 4 is part of the aggregated state 1. Therefore, those states that are outside of TAL that behave like SCs 4,7,10 and 13 on Fig. 4.4(a), belong to aggregated state 4 on Fig. 4.4(b). The same reasoning can be applied to the aggregated state 5.

As stated above, we model the UE dynamics through a discrete-time Markov chain, as shown in Fig. 4.5. With the transition matrix T, it is possible to obtain the fundamental matrix Z of the regular Markov chain [KS76] defined as follows:

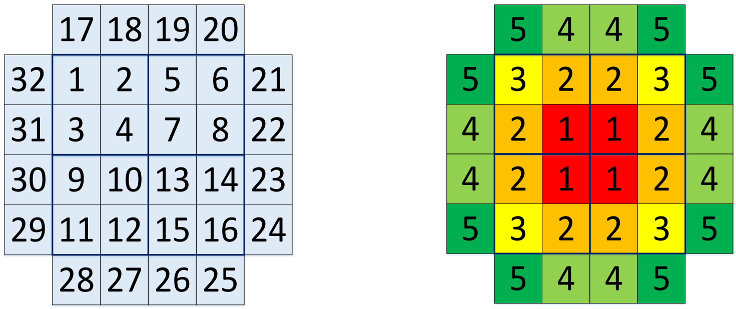
$$Z = (I - T + A)^{-1}, \tag{4.1}$$

where I is the identity matrix and $A = \lim_{k\to\infty} T^k$. It should be noted that the matrix A is composed by the steady state probability row vector Π repeated on each row. The mean number of visits to state j starting from state i after k steps is

$$\bar{Y}_{ij}^{k} = \sum_{n=0}^{k-1} t_{ij}^{(n)}, \tag{4.2}$$

According to [KS76] this expression in 4.2 can be simplified for large values of k as

$$\bar{Y}_{ij}^{k} = z_{ij} - a_{jj} + k \cdot a_{jj}. \tag{4.3}$$



(a) Cells inside the TAL and neighbors

(b) Aggregated diagram

Figure 4.4: State aggregation for TAL and neighbors.

The expression in 4.2 is suitable for large systems where obtaining the powers of T require a large computational cost, and in this work was used when the number of transitions between call arrivals was equal or higher than 30. Therefore, the mean number of TAL updates after k movements is

$$\overline{TAL}_c^k = \sum_{i \in \Omega, j \in \Gamma} \bar{Y}_{ij}^k \cdot \eta_i, \tag{4.4}$$

where Ω is the set of aggregated states that belong inside the TAL (1,2 and 3 in Fig. 4.5), Γ is the set of aggregated states adjacent to the TAL (4 and 5 in Fig. 4.5), and η_i is a weighting factor that represents the proportion of states that belong to the aggregated state i in relation to the total number of states that belong inside the TAL.

4.2.2 Mean number of TA updates after k movements

In the aggregation method described in the previous section all the states that belong to the same aggregated state have the same TA crossing probability. Hence, it is possible to use the same model to obtain $\overline{TA}_c^k$. However, to maintain consistency with the 3GPP specifications, TAL updates have precedence over TA updates. Therefore, when a user crosses both a TA and TAL, a TA

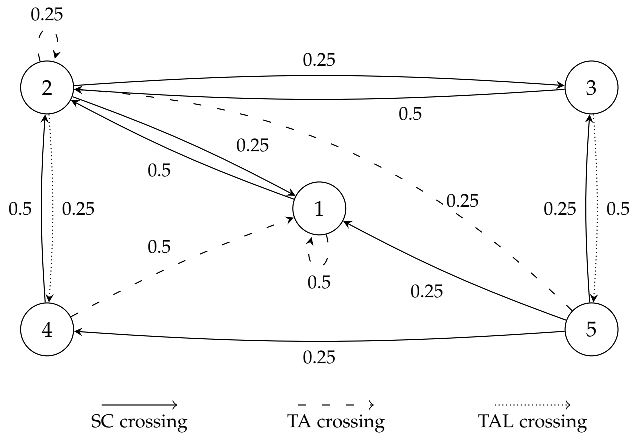


Figure 4.5: Aggregated Discrete-Time Markov chain for N=2, H=2, V=2.

update is not performed. Using the same transition matrix T defined for the aggregated system, the mean number of TA updates after k steps is

$$\overline{TA}_c^k = \sum_{i \in \Omega} \sum_{j \in \Theta, l \in \Psi(j)}^{n=1:k} t_{ij}^{(n-1)} \cdot t_{jl} \cdot \eta_i, \tag{4.5}$$

where Ω is the subset of aggregated states that belong inside the TAL, Θ is the subset of aggregated states that can perform a TA update without causing a TAL update, $\Psi(j)$ is the corresponding subset of aggregated states where the UE is leaving after a TA update is produced from state j, $t_{ij}^{(n-1)}$ is the probability of being in state j after $n-1$ steps with initial state i, t_{jl} is the probability of going from state j to state l, and η_i is as previously defined. For example, in the system in Fig. 4.4(b), Ω={1,2,3}, Θ={1,2,4,5},$\Psi(1)$={1}, $\Psi(2)$={2},$\Psi(4)$={1}, and $\Psi(5)$={2}.

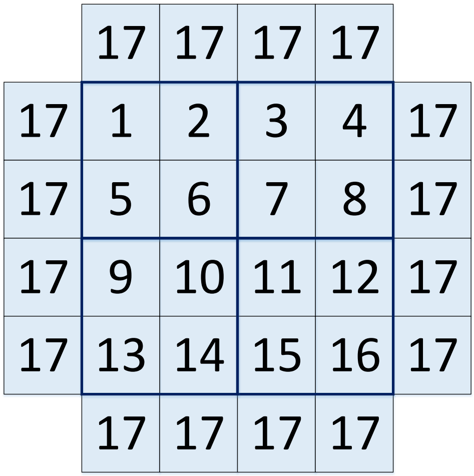


Figure 4.6: TAL surrounded by an absorbing state

4.2.3 Probability of remaining in the same area after k movements

The probabilities of ending in the same SC or the same TA are easily obtained by representing all the states in the system surrounded by an absorbing state, as shown in Fig. 4.6. Therefore, we have a system of NxVxNxH+1 states, where T is the corresponding transition matrix. Since the probability of starting the ECM-idle mode in SC i and being in the same SC after k movements is defined as $p_{SC}^{k}= t_{ii}^{(k)}$, the probability of starting the ECM-idle mode in any given TA and ending in the same TA after k steps, is given by

$$p_{TA}^{k} = \sum_{i \in \Delta} \sum_{j \in \Upsilon(i)} \frac{t_{ij}^{(k)}}{N^2 \cdot V \cdot H}, \tag{4.6}$$

where Δ is the set of SCs that belong inside the TAL, $\Upsilon(i)$ is the set of SCs that belong to the same TA as the initial SC i, and $1/(N^2 \cdot V \cdot H)$ is a weighting factor for all the SCs in the TAL.

Table 4.1: Cost associated to elements of the network.

	Cost Description	Cost
C_{CN}	Cost of routing to the MME	1
C_{X2}	Cost of routing to the X2-GW	1
C_{MME}	Processing cost of the MME	10
C_{LA}	Processing cost of the local anchor	2

4.3 Cost definition

In this section the cost function for the 3GPP scheme and the two X2-Interface-based schemes proposed is defined. It is composed by the location update cost and paging cost. In Table 4.1 we define the costs associated to different elements in the network are defined.

4.3.1 Location update cost

The mean cost of a location update to the MME after k UE movements is defined as

$$LU^{k}_{MME} = \overline{TAL}^{k}_{c}(C_{CN} + C_{MME}). \tag{4.7}$$

This cost is the same for the two proposed solutions and the 3GPP-based scheme.

The X2-Interface-based schemes include a LU cost related to the signaling sent whenever a SC or a TA is crossed. This signaling is processed by the LA, which is another SC from a functional point of view. Therefore, the location update costs for an SC update LU^{k}_{SC} and a TA update LU^{k}_{TA} after k steps are defined, respectively, as

$$LU^{k}_{SC} = (k - \overline{TAL}^{k}_{c})(2C_{X2} + C_{LA}), \tag{4.8}$$

$$LU^{k}_{TA} = \overline{TA}^{k}_{c}(2C_{X2} + C_{LA}), \tag{4.9}$$

where the factor (k-$\overline{TAL}_c^k$) is the mean number of SC crossings excluding those that involve a TAL update, and $2C_{X2}$ refers to the message that goes from the SC to the X2-GW and from the X2-GW to the LA.

4.3.2 Paging cost

The paging scheme used for the 3GPP-based scheme sequentially pages the last registered SC, then the SCs in the TA of the last registered SC, and finally all the SCs in the TAL. Therefore, the paging cost for the 3GPP-based scheme after k movements of the UE, $Paging_{REF}^k$, is defined as follows:

$$\begin{aligned} Paging_{REF}^k = (&p_{SC}^k + N^2(p_{TA}^k - p_{SC}^k) \\ &+ N^2 HL(1 - p_{SC}^k - (p_{TA}^k - p_{SC}^k))) \cdot C_{CN}. \end{aligned} \tag{4.10}$$

The paging procedures used by the X2-Interface-based schemes follow a three-step sequence. The MME pages the LA, then it identifies the last SC or TA registered, and finally forwards the paging message using the X2 Interface to the corresponding SC or TA. The paging cost for the SC update solution and the TA update solution are, respectively:

$$Paging_{X2-SC}^k = C_{CN} + C_{LA} + 2C_{X2}, \tag{4.11}$$

$$Paging_{X2-TA}^k = C_{CN} + C_{LA} + (N^2 + 1)C_{X2}. \tag{4.12}$$

4.3.3 Total cost

The total cost for the 3GPP-based scheme, and the two X2 Interface-Based schemes after k movements are shown in the following equations :

$$Cost_{REF}^k = LU_{MME}^k + Paging_{REF}^k, \tag{4.13}$$

$$Cost_{X2-SC}^k = LU_{MME}^k + LU_{SC}^k + Paging_{X2-SC}^k, \tag{4.14}$$

$$Cost^k_{X2-TA} = LU^k_{MME} + LU^k_{TA} + Paging^k_{X2-TA}. \tag{4.15}$$

4.4 Results

In this section, we evaluate the schemes proposed and compare their results with the 3GPP-based-schemes. Unless otherwise stated, the cost values used in the rest of the document are shown in Table 4.1. As it can be seen, the cost of using the backhaul to connect to the X2-GW is the same as the cost of connecting to the MME. This assumption is based on the fact that delay restrictions apply to both of them, given the characteristics of the backhaul. The processing cost of the MME is penalized, since large deployments of SCs represent a heavy load on the MME, and this entity is responsible for many other functions besides the idle mode location management. On the other hand, the LA is distributed among all the SC in the network, and therefore the processing cost is lower.

In Figures 4.7 and 4.8, the LU and paging costs are shown for the suggested solutions and the 3GPP-based scheme. TAs are composed of 4x4 SCs and TALs of three different sizes: 2x2, 3x3 and 4x4. These costs are evaluated against the mean number of transitions between calls, which indicates the mobility of the UE, and can be considered as the inverse of the Call-to-Mobility Ratio (CMR). As it is expected, as the mobility increases, so does the LU costs, and the highest cost belongs to the X2-Interface-based scheme with SC-based LU. The small reduction in LU cost for this scheme as the size of the TAL increases indicates that a small percentage of the LU cost is caused by LU to the MME. The lowest cost is obtained by the 3GPP reference solution, and this cost is reduced as the TAL size is increased.

The paging cost of the 3GPP-based scheme is the highest and it increases with the number of cells inside the TAL and the mean number of transitions between call arrivals. This value is bounded by the total number of SCs in the TAL to be paged. Also, the paging cost of the X2-Interface-based scheme

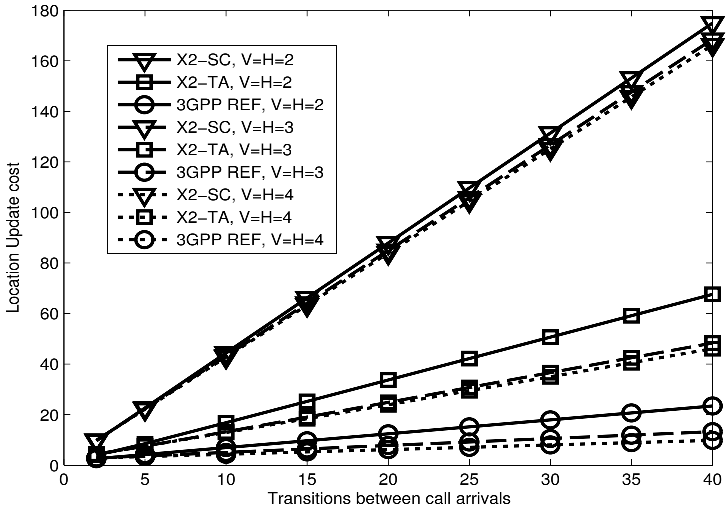


Figure 4.7: Location update cost for N=4 and various TAL sizes.

with SC-based LU is the lowest, since this procedure allows to know the exact position of the UE. As a consequence, the cost is the same for any mobility value.

In Figures 4.9 and 4.10, the LU and paging costs are shown for the suggested solutions and the 3GPP-based scheme. The TAL is composed by 3x3 TAs, and three sizes of TAs are compared. Again, the LU cost of the X2-Interface-based scheme with SC-based LU is the highest, and barely improves with TA size increments. The X2-Interface-based scheme with TA-based LU reduces its LU cost as the TA size increases. By increasing N from 4 to 6, the number of SC increases in 100%. Although the paging cost for the X2-Interface-based scheme with TA-based LU scheme does not grow as fast as the 3GPP-based scheme with N, it is not convenient to keep increasing the TA size, since the paging cost of the X2-Interface-based scheme with TA-based LU scheme when N=6 is higher than the cost of the 3GPP-based scheme when N=2.

In Fig. 4.11 we present the best possible results for the 3GPP-based scheme

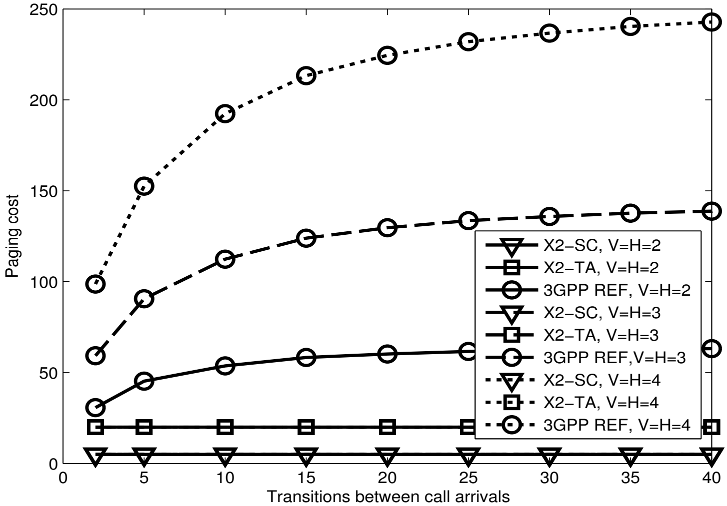


Figure 4.8: Paging cost for N=4 and changing TAL size.

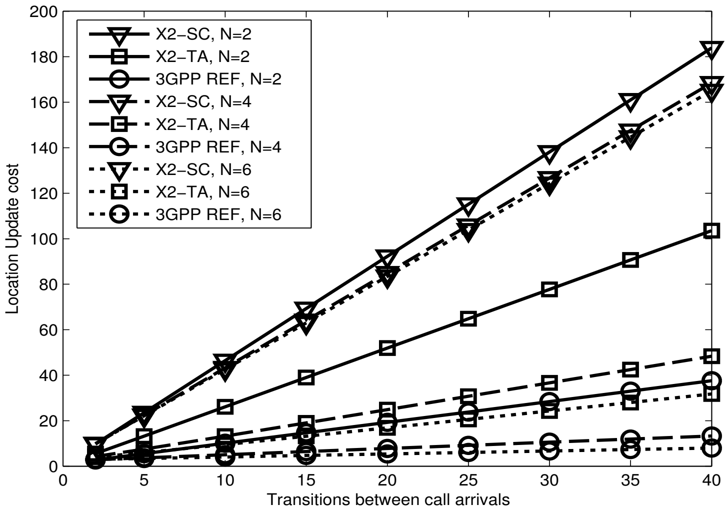


Figure 4.9: Location update cost for H=V=3 and various TA sizes.

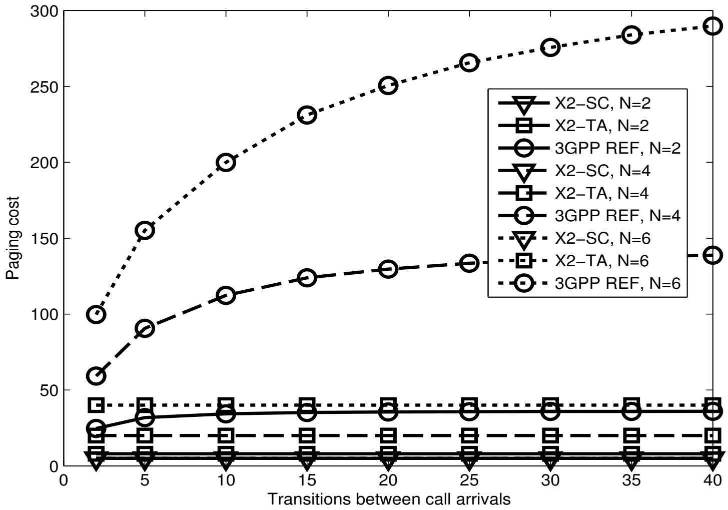


Figure 4.10: Paging cost for H=V=3 and various TA sizes.

and the X2-Interface-based scheme with TA-based LU for several TAL sizes. A reduction of up to 16% with respect to the 3GPP-bases scheme is achieved when H=V=4 is used. However no reduction is achieved if H=V=2, so TA size is very important for this solution.

Most of the total cost reduction achieved by X2-Interface-based schemes comes from paging. In LU, however, the reduction is achieved by avoiding the use of the MME. Nevertheless, this reduction is bounded by C_{X2}. In Fig. 4.12 we show the best solutions for a system with V=H=4, when the X2-Interface-based scheme with TA-based LU is used. By reducing C_{X2} the total cost is reduced, and this tends to increase with mobility rates. When the number of movements between arrivals is 40, the cost with C_{X2}=1 decreases around 10% and when C_{X2}=0.5 around 38%. Therefore, a C_{X2} reduction in 50% reduces the total cost four times. These results are really promising, specially when the signaling is done between neighbor SC or the X2-GW is located near the SC.

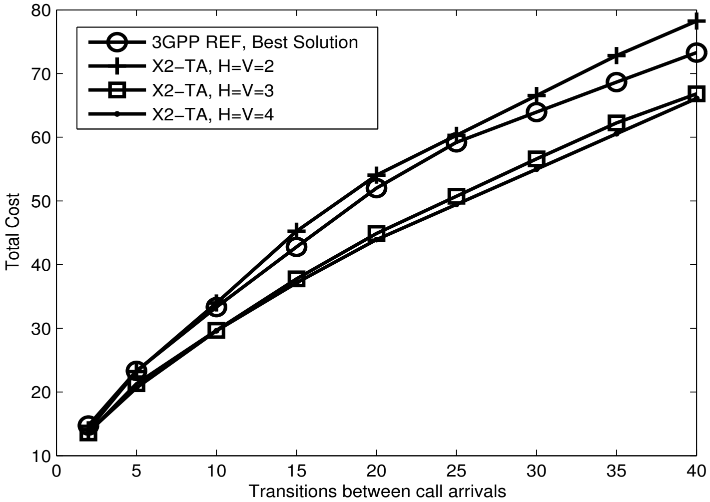


Figure 4.11: Total cost for N=M=2 and different V,H.

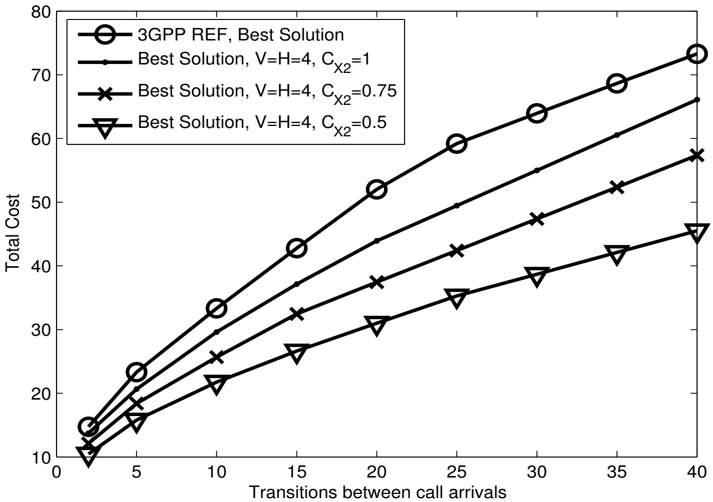


Figure 4.12: Best total cost solution fixing TAL size and varying TA size.

4.5 Conclusions

In this chapter we have approached the mobility problem for a multi-layered network, where a large deployment of small cells does not rely on a macrocell network. We have proposed two novel location update and paging schemes for small cell networks based on the TAL definition used traditionally in 3GPP. These schemes aim to reduce the paging cost incurred by using the 3GPP definition of TAL granularity for a user location. We do so by defining a local anchor that keeps track of users locations. This local anchor is a common small cell, and changes for each user. Hence, it is distributed among all the SC in the TAL. On the other hand, the proposed solutions aim to exploit the characteristics of the X2 Interface, which allows cells to connect without the control of the core network.

In contrast to the 3GPP-based scheme, by implementing X2-interface-based schemes that allow location update and paging procedures, it is possible to reduce the granularity without increasing the load in the mobility management entity in the core network. A Markov model is presented to evaluate the proposed solutions and compare their cost with the 3GPP-based scheme. Results show that when a small cell granularity is used, the location update cost raises, eliminating any improvement done by reducing the paging signaling. Moreover, by defining a Tracking Area granularity, it was possible to change the parameters of the deployment by increasing or decreasing the size of the Tracking Area List. This approach achieves a reduction in the total cost when compared to the 3GPP-based scheme. Additionally, it was observed that the proposed schemes perform better as users' mobility is increased. This is a desirable characteristic that suits the deployment of small cell networks.

As future work we aim to increase the functionality of the X2-interface for mobility, in terms of location management integration with macrocells and also for mobility management, since this function is also harmed by small cells characteristics.

Chapter 5

Conclusions

The concept of heterogeneous networks sets a frame to harmonically integrate several technologies in order to provide the best possible service in a continuously demanding environment. In particular, data growth has become the most demanding challenge in communications, and for mobile networks it is directly related with the popularity of smartphones and tablets. Hence, heterogeneous networks are proposed to face the need to make the most of concurrent technological advances in wireless communications. However, the coexistence of these technologies and its integration imposes new challenges that require more complex solutions. Three aspects of heterogeneous networks are studied in this thesis: radio resource management in a Multi-RAT network, access control with dynamic spectrum access and signaling load for location management in a multi-layer network.

In Chapter 2 we studied a CRRM problem, where JCAC and JHC functions are included. Two technologies (TDMA and WCDMA) and two services (voice and data) are available. The same model can be adapted to analyze OFDMA, which is used in technologies such as WiMAX or LTE. First, heuristic policies are described as a function of the analysis of several optimal policies found using dynamic programming. The main characteristics of the optimal policies were used to define two types of vertical handoff, which were used to construct new MDPs, optimized using the policy iteration method of dynamic programming. Analysis of optimal policies was done in order to describe new heuristics that use vertical handoff. This heuristic solutions are useful since they avoid the computational cost associated to find optimal solutions and also perform very closely to the optimal solutions in several scenarios. In order to overcome the computational cost issue associated to the traditional policy iteration method, two optimization methods were described. The solutions found using these proposed methods closely resemble the optimal solutions and were obtained in less time than traditional policy iteration. This cost reduction opens the possibility to model systems that include more RATs or more user types. Also, the proposed optimization methods can be used to solve other types of problems were user's events fulfill the time scale separation assumption, just like in the case of voice and data services.

In Chapter 3 we studied a CR system where SUs are compelled to vacate their channel when a PU arrives. To overcome forced termination, spectrum handover is implemented with integer and fractional guard channels. Analysis of the system is done over three parameters of secondary users: throughput, blocking probability and forced termination probability. Results show that the use of guard channels has the same impact as in cellular networks, where it limits the forced termination probability, but increases the blocking probability. An access control problem is proposed to find the number of optimal guard channels using a cost function that represents the trade-off between the blocking and forced termination probabilities. A second problem is also proposed to find the number of optimal guard channels when the forced termination probability is bounded. Analysis shows that the optimal number of guard channels is shaped by the number of SUs that can share a single PU channel, and that this value is always an integer.

In Chapter 4 we proposed two location management schemes for small cell deployments that are compatible with the 3GPP specifications. The proposed schemes use a local anchor that keeps a record of the current user location, while at the same time is perceived by the network as the current position. Since this local anchor is a regular small cell, the solution is distributed. On the other hand, the location update procedure uses the X2-interface, and therefore the interaction with the core network is reduced. This feature allows to reduce the granularity of a user location, which reduces the paging cost. However, updating the local anchor raises the location update cost, and therefore a trade-off problem arises. However, results showed that the proposed solutions reduce the overall cost in relation to the 3GPP proposal, which is promising considering the importance of location management functions.

The future of heterogeneous networks aims to increase integration, and this will affect every aspect of current cellular networks. In order to successfully approach this problem, it is expected that new and advanced traffic management methods are provided. Usually, this means that more intelligence is expected from the network in order to adapt to the conditions of the environment. CR inherently follows this approach, but other functions like CRRM will have to adapt in order to respond to user's and network's dynamics. All this capabilities can be enhanced in a multi layer scenario where direct coordination among cells is promoted, without the intervention of the core network. This distribution of functions opens new possibilities to enhance performance while it simplifies adaptation. Therefore, future work will be in enhancing procedures and functions that can easily adapt to user's changing requirements.

Appendices

Appendix A

Abbreviations and acronyms

3GPP	3rd Generation Partnership Project
BS	Base Station
CHT	Channel Holding Time
CMR	Call to Mobility Ratio
CR	Cognitive Radio
CRT	Cell Residence Time
CTMC	Continuous-Time Markov Chain
CV	Coefficient of Variation
CR	Cognitive Radio
CS	Complete Sharing
DCA	Dynamic Channel Allocation
FCA	Fixed Channel Allocation
FCC	Federal Communication Commission
FDMA	Frequency Division Multiple Access
FGC	Fractional Guard Channel
GC	Guard Channel
GPRS	General Packet Radio Service
GSM	Groupe Spécial Mobile / Global System for Mobile Communications
JCAC	Joint Call Admission Control

JCC	Joint Congestion Control
JHC	Joint Handover Control
JPS	Joint Packet Scheduling
JPM	Joint Power Management
LA	Local Anchor
LTE	Long Term Evolution
LU	Location Update
NGMN	Next Generation Mobile Networks
MDP	Markov Decision Process
MGC	Multiple Guard Channel
MFGC	Multiple Fractional Guard Channel
MME	Mobility Management Entity
MT	Mobile Terminal
OFDMA	Orthogonal Frequency-Division Multiple Access
PN	Primary Network
PU	Primary User
QAM	Quadrature Amplitude Modulation
QBD	Quasi Birth and Death Process
QoS	Quality of Service
RRM	Radio Resource Management
RRU	Radio Resource Unit
RB	Resource Block
SAC	Session Admission Control
SC	Small Cell
SH	Spectral Handover
SIR	Signal to Interference Ratio
SMPD	Semi-Markov Decision Process
SON	Self-Optimizing Networks
SN	Secondary Network
SU	Secondary User
TA	Tracking Area
TAI	Tracking Area Identifier

TAL	Tracking Area List
TDMA	Time Division Multiple Access
UE	User Equipment
UMTS	Universal Mobile Telecommunications Service
WCDMA	Wideband Code Division Multiple Access
WiMAX	Worldwide Interoperability for Microwave Access

Appendix B

Teletraffic Analysis

The assumptions used in this work are well known in teletraffic theory, such as considering an infinite population of users, reaching a steady state operation point or event independence. These assumptions allows us to maintain the focus of our work in the AC and resource management problems by defining a model that reduces the inherent complexity of telecommunication systems and therefore reduce the computational cost associated to its analysis. The same could be said about other considerations such as an homogeneous cell size and traffic distribution in mobility. The appropriateness of these assumptions has been addressed in e.g. [Min93], [KS01] and therefore any assumption is clearly stated.

B.1 Traffic parameters

B.1.1 Inter-arrival time

One of the main parameters of the system is the inter-arrival time, used to characterize the arrival of a new user into the system. Considering that each arrival is independent and identically distributed (iid), we define τ as the inter-arrival time random variable (r.v.). For mathematical tractability, an exponential distribution is commonly used to describe this r.v., and this is assumed in this work. However, in order to broaden the reach of this analysis, hyper-exponential and erlang distributions are also used.

B.1.2 Service time

Another important parameter to define a teletraffic system is the service time. This value sets the amount of time that a user occupies the resources of the system, and therefore is technology and service dependent [HR04] , [KZ97],[XT03]. Although this work assumes exponential distribution, some works do not validate this hypothesis [LC97],[HSSK01]. As in the case of inter-arrival times, Hyper-exponential and Erlang distributions are also used.

B.1.3 Cell residence time

The cell residence time defines the amount of time a users spends in a particular cell before leaving to another. Therefore, it is a crucial parameter to analyze mobility in cellular networks and its values heavily relies on the geometry of cells.

Appendix C

Markov decision process

In decision problems, a particular case that fulfills the Markov property is defined as a Markov decision process. Since this type of problems consist in choosing the best option for each state, the Markov property in this context states that the decision in a particular state is independent from the previously visited states. This means that all the necessary information to make a decision is available in the current state. A Markov decision process is defined by its state space set S, the action set A, and both the rewards and probabilities of going from the current state to other states, which are action dependent. In particular, we are interested in finite Markov decision processes, where the finite term makes reference to the size of the state space. The states s in S are defined so they provide enough information about the system to make decisions. These decisions are represented in MDPs by the set of actions A. The subset of possible actions A_s refers to the actions that can be taken in state s. On the other hand, the transition probabilities, that is, the probability of going from the current state $s$to a possible state s' is given by

$$P_{ss'}(a) = p(s_{t+1} = s' | s_t = s, a_t = a), \tag{C.1}$$

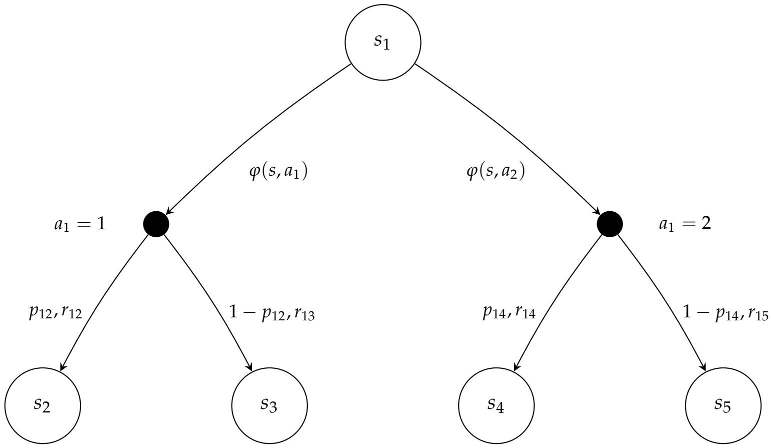


Figure C.1: Markov decision process transition

and the immediate reward for going from current state s to a given state s' is defined as

$$R_{ss'}(a) = E(r_{t+1}|s_t = s, a_t = a, s_{t+1} = s'), \tag{C.2}$$

where t is the time when the decision is made. When a transition can occur at any time, we have a continuous time Markov decision process. On the other hand, when the decision times are discrete, we have a discrete time Markov decision process. The objective of an MDP is to find the set of actions a_s for each state in S that optimize the total expected revenue. A policy Ψ associates the actions A on each state in S, defining a specific Markov process. Hence, the optimal policy Ψ^* sets a Markov process which maximizes the average revenue. This is shown in Fig C.1, where action 1 is taken with probability $\varphi(s, a_1)$ and action 2 is taken with probability $\varphi(s, a_2)$, and $\varphi(s, a_1)$+$\varphi(s, a_2)$=1. After action 1 is taken, the next state will be s_2 with probability p_{12} and state s_3 with probability $1 - p_{12}$ and this affects the obtained revenue r.

Value functions $V^{\Psi}(s)$ estimate the future revenues of being in a given state s, using action a and following a policy Ψ for future states. This is represented by:

$$V^{\Psi}(s) = \sum_{a} \varphi(s,a) \sum_{s'} P_{ss'}(a)(R_{ss'}(a) + \gamma V^{\Psi}(s')), \tag{C.3}$$

where $0 \leq \gamma \leq 1$ is the discount factor. Equation (C.3) is the Bellman equation for value functions and it relates the value of being in state s with future values. This equation can be solved iteratively.

C.1 Dynamic programming

The main characteristic of dynamic programming [Bel57] [Ber01] is the ability to find an optimal solution of a problem by dividing it into smaller problems. This is represented by the Bellman optimality equation [Bel57], which defines the optimal policy in terms of the value functions V^* as

$$V^*(s) = \max_{a} \Big\{ \sum_{s'} P_{ss'}(a)(R_{ss'}(a) + \gamma V^*(s')) \Big\}, \tag{C.4}$$

where the immediate returns obtained in state s are related to the value function of the optimal policy V^*. Hence, it can be seen that by having V^*, the best decision for each state in S can be found in a state by state basis, hence dividing a large problem into smaller problems.

C.1.1 Policy iteration

Policy iteration is a dynamic programming method that can search among the finite group of possible policies for the MDP and find the optimal policy Ψ^* in a finite number of steps. Since V^* is unknown, the first step of policy iteration consists in defining an arbitrary initial policy Ψ_{ini} and finding its value function $V^{\Psi_{ini}}$ in a step defined as policy evaluation. Once this value is obtained, this policy is enhanced based on (C.4). This process is repeated until no further improvement can be done, i.e., the optimal policy Ψ^* is found.

An important characteristic of this method is that it usually finds the optimal solution in a few iterations [SB98]. In [How58], Howard proposed policy iteration in order to find the optimal policy without explicitly using Bellman optimality equation. This involves the use of relative values v which for the case of a discrete time MDP are defined as the difference between the expected value function and the average revenue of the policy as:

$$v_s^{\Psi} = \lim_{n\to\infty} (V_n^{\Psi}(s) - n \cdot R^{\Psi}), \tag{C.5}$$

where n represents the time in discrete steps, and R^{Ψ} is the mean revenue when using the policy Ψ. The relative values associate the revenues obtained on each state with the average expected revenue of a given policy Ψ. This is done using Howard's equation as:

$$\vec{R}(\Psi) - R^{\Psi} \cdot e + v^{\Psi}(T^{tr}(\Psi) - I) = 0, \tag{C.6}$$

where $\vec{R}(\Psi)$ is the vector of revenues for each state, and $T(\Psi)$ is the infinitesimal generator of the Markov chain associated to policy Ψ. Hence, (C.6) is used to find the relative values v^{Ψ} without the steady state probabilities of the Markov chain defined by policy Ψ.

The continuous time equivalent of (C.6) is:

$$\vec{R}(\Psi) - R^{\Psi} \cdot e + v^{\Psi} Q^{tr}(\Psi) = 0, \tag{C.7}$$

where $\vec{R}(\Psi)$ is the vector of revenue rates for each state, and $Q(\Psi)$ is the infinitesimal generator of the Markov process associated to policy Ψ.

Using (C.6) and (C.7) it is possible to perform *policy evaluation*, that is, to calculate the relative values of a discrete time or continuous time MDP, given a random policy Ψ. The next step consists in improving the current policy, in a step known as *policy improvement*. For the discrete time MDP, this is done by choosing the best possible action on each state as:

$$a_s = \max_a \left\{ R_s(a) - R^{\Psi} + \sum_{s'} t_{ss'}(a) v_{s'}^{\Psi} \right\}, \tag{C.8}$$

where $R_s(a)$ is the cost of choosing action a in state s, $t_{ss'}$ is the transition probability of going from state s to state s' when choosing action a and policy Ψ, and $v_{s'}(a)$ is the relative value of state s' using policy Ψ. The resulting policy, $\Psi^{'}$, is as good or better than Ψ, according to (C.4). The continuous time equivalent of (C.8) is

$$a_s = \max_a \left\{ R_s(a) - R^{\Psi} + \sum_{s' \neq s} q_{ss'}(a)(v_{s'}^{\Psi} - v_s^{\Psi}) \right\}, \qquad \text{(C.9)}$$

where $q_{ss'}$ is the transition rate of going from state s to state s' when choosing action a and policy Ψ.

In Table C.1 we describe the policy iteration method for the discrete and continuous time MDPs respectively. It can be seen that the two methods only differ in the use of the equations, although the fact that the steady state probability of discrete time Markov chains can be calculated iteratively has some advantages to solve MDPs as will be seen in chapter 2. Another important fact is that policy iteration implies solving linear systems of a size as big as the number of states that compose the MDP, resulting in what Bellman called the curse of dimensionality. This and other considerations are mentioned throughout this work.

Table C.1: Policy iteration algorithm .

Step 1.	Choose an arbitrary policy Ψ_{ini}
Step 2.	Set the first relative value $v^{\Psi_{ini}}(0)$=0
Step 3.	Calculate relative values $v_{\Psi_{ini}}$ and the mean revenue $R^{\Psi_{ini}}$ for the initial policy Ψ_{ini} using expression (C.6) for the discrete time MDP and (C.7) for the continuous time MDP.
Step 4.	Using $v_{\Psi_{ini}}$ and $R^{\Psi_{ini}}$ found in the previous step find the action a_s for each state in S that maximizes the expression in (C.8) or (C.9). The resulting policy is called Ψ_{new}.
Step 5.	If the resulting policy Ψ_{new} differs from the initial policy Ψ_{ini}, go back to step 2, using Ψ_{new} as the initial policy. If not, Ψ_{new} is the optimal policy.

Appendix D

Publications

D.1 Related with this thesis

D.1.1 Journal

1. Diego Pacheco-Paramo, Vicent Pla, Vicente Casares-Giner, and Jorge Martinez-Bauset.
   Optimal Radio Access Technology Selection on Heterogeneous Networks, Physical Communication, Vol. 5, Issue 3, pp. 253-271. 2012.

2. Jorge Martinez-Bauset, Vicent Pla, M. Jose Domenech-Benlloch, and Diego Pacheco-Paramo.
   Admission Control and Interference Management in Dynamic Spectrum Access Networks, EURASIP Journal on Wireless Communications and Networking, Springer. Vol. 2010.

3. Jorge Martinez-Bauset, Vicent Pla and Diego Pacheco-Paramo.
   Comments on analysis of cognitive radio spectrum access with optimal channel reservation, IEEE Communication Letters, Vol. 13, Issue

10, pp. 739-739. 2009.

D.1.2 International conferences

1. Diego Pacheco-Paramo, Ian F. Akyildiz, and Vicente Casares-Giner. **X2-Interface-Based Location Management for Small Cell Networks**, In Proceeding of GLOBECOM'13 - global communications conference, Atlanta, Georgia, USA, 9-13 December, 2013.

2. Diego Pacheco-Paramo, Jorge Martinez-Bauset, Vicent Pla, and Elena Bernal-Mor. **First Iteration Policies for Admission Control in Multiaccess Networks**, In Proceeding of EUROPEAN WIRELESS'13 - 19th European Wireless Conference, Guildford, UK, 16-18 April, 2013.

3. Diego Pacheco-Paramo, Vicent Pla, Vicente Casares-Giner, and Jorge Martinez-Bauset. **Optimal Joint Call Admission Control With Vertical Handoff on Heterogeneous Networks**, In Proceeding of NETWORKING'11, Tenth International IFIP TC 6 Networking Conference, Valencia, Spain. Lecture Notes in Computer Science (LNCS) Springer-Verlag, Vol. 6641, pp. 121-134, May 2011.

4. Diego Pacheco-Paramo, Vicent Pla, and Jorge Martinez-Bauset. **Optimal Admission Control in Cognitive Radio Networks**, In Proceeding of CROWNCOM'09 - The 4th international conference on Cognitive Radio Oriented Wireless Networks and Communications, Hannover, Germany, 22-24 June, 2009.

D.2 Other publications

D.2.1 International conferences

1. Vicente Casares-Giner, Patrick Wüchner, Diego Pacheco-Paramo, and Hermann de Meer.
   Combined Contention and TDMA-Based Communication in Wireless Sensor Networks, In 8th Euro-NGI conference on Next Generation Internet, Karlskrona, Sweden, 25-27 June 2012.

Appendix E

Research projects related to this thesis

This work has been developed in the framework of the following national and international projects:

- Spanish government project COHWAN (Cooperative and Opportunistic Wireless Heterogeneous Access Networks). January 2011- December 2013.
- Euro NF Network of Excellence "Anticipating the Network of the Future - From Theory to Design" specific joint research project PADU (Performance and Durability of Future Wireless Sensor Networks). January 2008 - June 2012.
- Spanish government project IRAMCEL (Ad Hoc, Mesh and Cellular Networks Integration). October 2007 - September 2010
- Security, services, networking and performance of next generation IP-based multimedia wireless Networks, S2EuNet (European Commission under the FP7/People/IRSES action)

Finally, we thank the support from the Spanish Government through the scholarship *Formación de Personal Investigador* (FPI) with reference BES-2009-013162.

Bibliography

[3GP12a] 3GPP, *3gpp tr 37.803: Universal mobile telecommunications system (umts) and lte; mobility enhancements for home node b (hnb) and home enhanced node b (henb)*, December 2012.

[3GP12b] 3GPP, *3gpp ts 36.420: Evolved universal terrestrial radio access network (e-utran); x2 general aspects and principles*, September 2012.

[ACD+12] J. Andrews, H. Claussen, M. Dohler, S. Rangan, and M. Reed, *Femtocells: Past, present, and future*, IEEE JSAC, Special Issue on Recent Advances **30** (2012), no. 3, 497–508.

[AGSA08] A. Attar, S. Ghorashi, M. Sooriyabandara, and A. Aghvami, *Challenges of real-time secondary usage of spectrum*, Computer Networks **52** (2008), no. 4, 816–830.

[AHL96] I. Akyildiz, J. Ho, and Y. Lin, *Movement-based location update and selective paging for pcs networks*, IEEE/ACM Transactions on Networking **4** (1996), no. 4, 629–638.

[ALVM08] I. Akyildiz, W. Lee, M. Vuran, and S. Mohanty, *A survey on spectrum management in cognitive radio networks*, IEEE Communications Magazine **46** (2008), no. 4, 40–48.

[ASPRG04] R. Agusti, O. Sallent, J. Perez-Romero, and L. Giupponi, *A fuzzy-neural based approach for joint radio resource management in a beyond 3g framework*, in proceedings of 1st International Conference on Quality of Service in heterogeneous in Wired/Wireless networks (2004), 216–224.

[BC89] D. Bertsekas and D. Castanon, *Adaptive aggregation for infinite horizon dynamic programming*, IEEE Transactions on automatic control **34** (1989), no. 6, 589–598.

[Bel57] R. Bellman, *Dynamic programming*, Princeton University Press, 1957.

[Ber01] D.P. Bertsekas, *Dynamic programming and optimal control*, Athena Scientific, 2001.

[BS97] S. Biswas and B. Sengupta, *Optimal admission control policies in multiservice cellular networks*, Call admissibility for multirate traffic in wireless ATM networks **2** (1997), 649–657.

[BSKD06] Y. Ben-Shimol, I. Kitroser, and Y. Dinitz, *Two-dimensional mapping for wireless ofdma systems*, IEEE Transactions on Broadcasting **52** (2006), no. 3, 388–396.

[CAG08] V. Chandrasekhar, J. Andrews, and A. Gatherer, *Femtocell networks: a survey*, IEEE communications magazine **46** (2008), no. 9, 59–67.

[CGMO98] V. Casares-Giner and J. Mataix-Oltra, *On movement-based mobility tracking strategy-an enhanced version*, IEEE Communication Letters **2** (1998), no. 2, 45–47.

[Com05] S.S.C. (Shared Spectrum Company), *Spectrum occupancy measurements 2005*, SSC, 1595 Spring Hill Rd, Suite 110, Vienna, VA 22182, USA, Tech. Rep., 2005. [Online]. Available: http://www.sharedspectrum.com/measurements/ (2005).

[Com07] ______, *Spectrum occupancy measurements 2007*, SSC, 1595 Spring Hill Rd, Suite 110, Vienna, VA 22182, USA, Tech. Rep., 2005. [Online]. Available: http://www.sharedspectrum.com/measurements/ (2007).

[DJVE13] Pacheco-Paramo D., Martinez-Bauset J., Pla V., and Bernal-Mor E., *First iteration policies for admission control in multiaccess networks*, Proceedings of European Wireless 2013 (2013).

[DVJ09] Pacheco-Paramo D., Pla V., and Martinez-Bauset J., *Optimal admission control in cognitive radio networks*, in proceedings of Cognitive Radio Oriented Wireless Networks and Communications, COHWAN'09 (2009).

[DVVJ11] Pacheco-Paramo D., Pla V., Casares-Giner V., and Martinez-Bauset J., *Optimal joint call admission control with vertical handoff on heterogeneous networks*, Proceedings of the 10th international IFIP TC 6 conference on Networking (2011).

[DVVJ12] ______, *Optimal radio access technology selection on heterogeneous networks*, Physical Communication **5** (2012), no. 3, 253–271.

[EE99] J. Evans and D. Everitt, *Effective bandwidth-based admission control for multiservice cdma cellular networks*, IEEE Transactions on Vehicular Technology **48** (1999), no. 1, 36–46.

[FC06] O. Falowo and H. Chan, *Fuzzy logic based call admission control for next generation wireless networks*, in proceedings of 3rd International Symposium on Wireless Communication Systems (2006), 574–578.

[FC08] O. Falowo and H. Anthony Chan, *Joint call admission control algorithms: requirements, approaches, and design considerations*, Computer Communications **31** (2008), 1200–1217.

[ff10] femto forum, *Femtocells- natural solution for offload, a femto forum topic brief*, femto forum, 2010.

[FMB12] J. Ferragut and J. Mangues-Bafalluy, *A self-organized tracking area list mechanism for large-scale networks of femtocells*, in Proceedings of IEEE International Conference on Communications (ICC 2012) (2012).

[FMBNMZ12] J. Ferragut, J. Mangues-Bafalluy, J. Nunez-Martinez, and F. Zdarsky, *Traffic and mobility management in networks of femtocells*, Mobile Networks and Applications **17** (2012), no. 5, 662–673.

[GJP$^+$91] K. Gilhousen, I. Jacobs, R. Padovani, A. Viterbi, L. Weaver, and C. Wheatley, *On the capacity of a cellular cdma system*, IEEE Transactions on Vehicular Technology **40** (1991), no. 2.

[GPRSA08] X. Gelabert, J. Perez-Romero, O. Sallent, and R. Agusti, *A markovian approach to radio access technology selection in heterogeneous multiaccess/multiservice wireless networks*, IEEE Transactions on Mobile Computing **7** (2008), no. 10.

[Gra77] W.K. Grassman, *Transient solutions in markovian queueing systems*, Computers and Operations Research **4** (1977), no. 1, 47–53.

[GS08] P. Goyal and S. Saxena, *A dynamic decision model for vertical handoffs across heterogeneous wireless networks*, in Proceedings of World Academy of Science, Engineering and Technology **31** (2008).

[HA96] J. Ho and I. Akyildiz, *Local anchor scheme for reducing signaling costs in personal communications networks*, IEEE/ACM Transactions on Networking **4** (1996), no. 5, 709–725.

[HNH05] A. Hasswa, N. Nasser, and H. Hassanein, *Generic vertical handoff decision function for heterogeneous wireless networks*, in Proceedings of 2nd IFIP International Conference on Wireless and Optical Communications Networks (2005), 239–243.

[How58] R. Howard, *Studies in discrete dynamic programming*, Massachusets Institute of Technology, 1958.

[HR04] D. Hong and S. Rappaport, *Traffic model and performance analysis for cellular mobiler adio telephone systems with prioritized and nonprioritized handoff procedures*, IEEE Transactions on Vehicular Technology **53** (2004), no. 2, 77–92.

[HSSK01] H. Hidaka, K. Saitoh, N. Shinagawa, and T. Kobayashi, *Teletraffic characteristics of cellular communication for different types of vehicle motion*, IEICE Transactions on Communications **E84-B** (2001), no. 3, 558–565.

[Inc13] Cisco Systems Inc, *Cisco visual networking: Index global mobile data traffic forecast update, 2012-2017*, Cisco White Paper, 2013.

[Jai68] N. Jaiswal, *Priority queues*, Academic Press, New York (1968).

[JVD09] Martinez-Bauset J., Pla V., and Pacheco-Paramo D., *comments on analysis of cognitive radio spectrum access with optimal channel reservation*, IEEE Communication letters **13** (2009), no. 10, 739–739.

[JVMD10] Martinez-Bauset J., Pla V., Domenech-Benlloch M., and Pacheco-Paramo D., *Admission control and interference management in dynamic spectrum access networks*, EURASIP Journal on Wireless Communications and Networking (2010).

[KCH04] D. Karabudak and B. Bing C. Hung, *A call admission control scheme using genetic algorithms*, ACM Symposium on Applied Computing (2004), 1151–1158.

[KR02] I. Koffman and V. Roman, *Broadband wireless access solutions based on ofdm access in ieee 802.16*, IEEE Communications Magazine **40** (2002), no. 4, 96–103.

[KS76] J. Kemeny and J. Snell, *Finite markov chains*, Springer-Verlag, 1976.

[KS01] K.Mitchell and K. Sohraby, *An analysis of the effects of mobility on bandwidth allocation strategies in multi-class cellular wireless networks*, Proceedings of IEEE INFOCOM **2** (2001), 1075–1084.

[KS04] K.Chiang and N. Shenoy, *A 2-d random-walk mobility model for location-management studies in wireless networks*, IEEE Transactions on Vehicular Technology (2004).

[KZ97] F. Khan and D. Zeghlache, *Effect of cell residence time distribution on the performance of cellular mobile networks*, Proceedings of IEEE VTC'97 (1997), 949–953.

[Lab12] Ericsson Labs, *Heterogeneous networks: Meeting mobile broadband expectations with maximum efficiency*, Ericsson White Paper, 2012.

[LC97] Y. Ling and I. Chlamtac, *Effects of erlang call holding times on pcs call completion*, Proceedings of INFOCOM' 97 (1997).

[LL12] R. Liou and Y. Lin, *Mobility management with the centralbased location area policy*, Computer Networks (2012).

[Min93] D. Minoli, *Broadband network analysis and design*, Artech House, 1993.

[MTM$^+$06] M.A. McHenry, P.A. Tenhula, D. McCloskey, D.A. Roberson, and C.S. Hood, *Chicago spectrum occupancy measurements & analysis and a long-term studies proposal*, in TAPAS 2006: Proceedings of the first international workshop on Technology and policy for accessing spectrum. New York,NY. USA, ACM. (2006).

[OARH06] Boxma O., Gabor A., Nunez-Quejia R., and Tan H., *Performance analysis of admission control for integrated services with minimum rate guarantees*, 2nd Conference on Next Generation Internet Design and Engineering, NGI' 06 (2006).

[OK92] T. Ott and K. Krishnan, *Separable routing: A scheme for state dependent routing of circuit switched telephone traffic*, Annals of Operations Research **35** (1992), no. 1, 43–68.

[PCG03] V. Pla and V. Casares-Giner, *Optimal admission control policies in multiservice cellular networks*, in Proceedings of the International Network Optimization Conference (INOC) (2003), 466–471.

[PCG05] ______, *Analysis of priority channel assignment schemes in mobile cellular communication systems: a spectral theory approach*, Performance Evaluation **59** (2005), no. 2–3, 199–224.

[PDJMT04] A. Pillekeit, F. Derakhshan, E. Jugl, and A. Mitschele-Thiel, *Force-based load balancing in co-located umts/gsm networks*, IEEE 60th Vehicular Technology Conference (2004), 4402–4406.

[PMBCG08] V. Pla, J. Martinez-Bauset, and V. Casares-Giner, *Comments on call blocking probability and bandwidth utilization of ofdm subcarrier allocation in next-generation wireless networks*, IEEE Communications Letters **12** (2008), no. 5, 349.

[PS82] C. Paige and M. Saunders, *Lsqr: An algorithm for sparse linear equations and sparse least squares*, ACM Transactions on Mathematical Software (1982).

[PS11] Ch. Paik and Y.S. Suh, *Generalized queueing model for call blocking probability and resource utilization in ofdm wireless networks*, IEEE Communications Letters **15** (2011), no. 7, 767–769.

[RNT97] R. Ramjee, R. Nagarajan, and D. Towsley, *On optimal call admission control in cellular networks*, Wireless Networks Journal (WINET) **3** (1997), no. 1, 29–41.

[Ros89] K. W. Ross, *Randomized and past-dependent policies for markov decision processes with multiple constraints*, Operations Research **37** (1989), no. 3, 474–477.

[RYGM10] S. Ravazi, D. Yuan, F. Gunnarson, and J. Moe, *Exploiting tracking area list for improving signaling overhead in lte*, Proceedings of Vehicular Technology Conference (2010).

[SB98] R. Sutton and A. Barto, *Reinforcement learning. an introduction*, A Bradford Book. The MIT Press., 1998.

[SCD06] K. Suleiman, A. Chan, and M. Dlodlo, *Load balancing in the call admission control of heterogeneous wireless networks*, International Wireless Communications and Mobile Computing Conference (2006), 245–250.

[Shl10] O. Shlakhter, *Acceleration of iterative methods for markov decision processes*, Thesis (2010).

[SNW06] E. Stevens-Navarro and V. Wong, *Comparison between vertical handoff decision algorithms for heterogeneous wireless networks*, IEEE Vehicular Technology Conference (2006), 947–951.

[SS85] P. Schweitzer and A. Seidmann, *Generalized polynomial approximations in markovian decision processes*, Journal of mathematical analysis and applications **110** (1985), no. 2, 568–582.

[THH02] A. Tolli, P. Hakalin, and H. Holma, *Performance evaluation of common radio resource management*, IEEE International Conference on Communications (ICC) **5** (2002), 3429–3433.

[Uni12] ITU. International Telecommunication Union, *Spectrum occupancy measurements and evaluation. report itu-r sm.2256*, International Telecommunication Union. [online]. Available: http://www.itu.int/pub/R-REP-SM.2256-2012, 2012.

[vLAV01] J. van Leeuwaarden, S. Aalto, and J. Virtamo, *Load balancing in cellular networks using first policy iteration*, Technical Report, Networking Laboratory,Helsinki University of Technology. (2001).

[WS07] L. Wu and K. Sandrasegaran, *A survey on common radio resource management*, The 2nd conference on Wireless Broadband and U-Wideband Communications, AusWireless, (2007).

[XT03] A. Xhafa and O. Tonguz, *Does mixed lognormal channel holding time affect handover performance of guard channel scheme?*, Proceeding of IEEE GLOBECOM' 03 (2003), 3452–3456.

[YK04] Fei Yu and Vikram Krishnamurthy, *Optimal joint session admission control in integrated wlan and cdma cellular networks with vertical handoff*, IEEE Transactions on Mobile Computing **6** (2004), 126–139.

[ZS05] C. Zobel and W. Scherer, *An empirical study of policy convergence in markov decision process value iteration*, Computers and Operations Research **32** (2005), no. 1.

[ZSY07] X. Zhu, L. Shen, and T. Yum, *Analysis of cognitive radio spectrum access with optimal channel reservation*, IEEE Communications Letters **11** (2007), no. 4, 304.

[ZWdO09] Z. Zhao, S. Weber, and J. de Oliveira, *Preemption rates for a parallel link loss network*, Performance Evaluation **66** (2009), no. 1, 21–46.